Random Noise Suppression Using Normalized Convolution Filter

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Summary

Random noise in seismic data hampers seismic interpretation, confounds automatic pickers, overprints seismic attributes, and masks subtle geologic features of interest. For this reason much of seismic processing is devoted to increasing the signal to noise ratio. In this paper, we introduce a novel method named the normalized convolution, or NC filter, which is based on a confidence estimation of the signal, to improve our signal to noise ratio. The NC filter attenuates noise and enhances the continuity of seismic events. We demonstrate the effectiveness of the filter on simple synthetic, a real data set contaminated with real band-limited seismic noise, and a real data set contaminated with high amplitude artificial noise. These examples suggest that the proposed method is ready for application to seismic data.

Theory

Normalized convolution was introduced as a general method for interpolating missing and uncertain data. This method can be viewed as locally solving a weighted least squares problem.

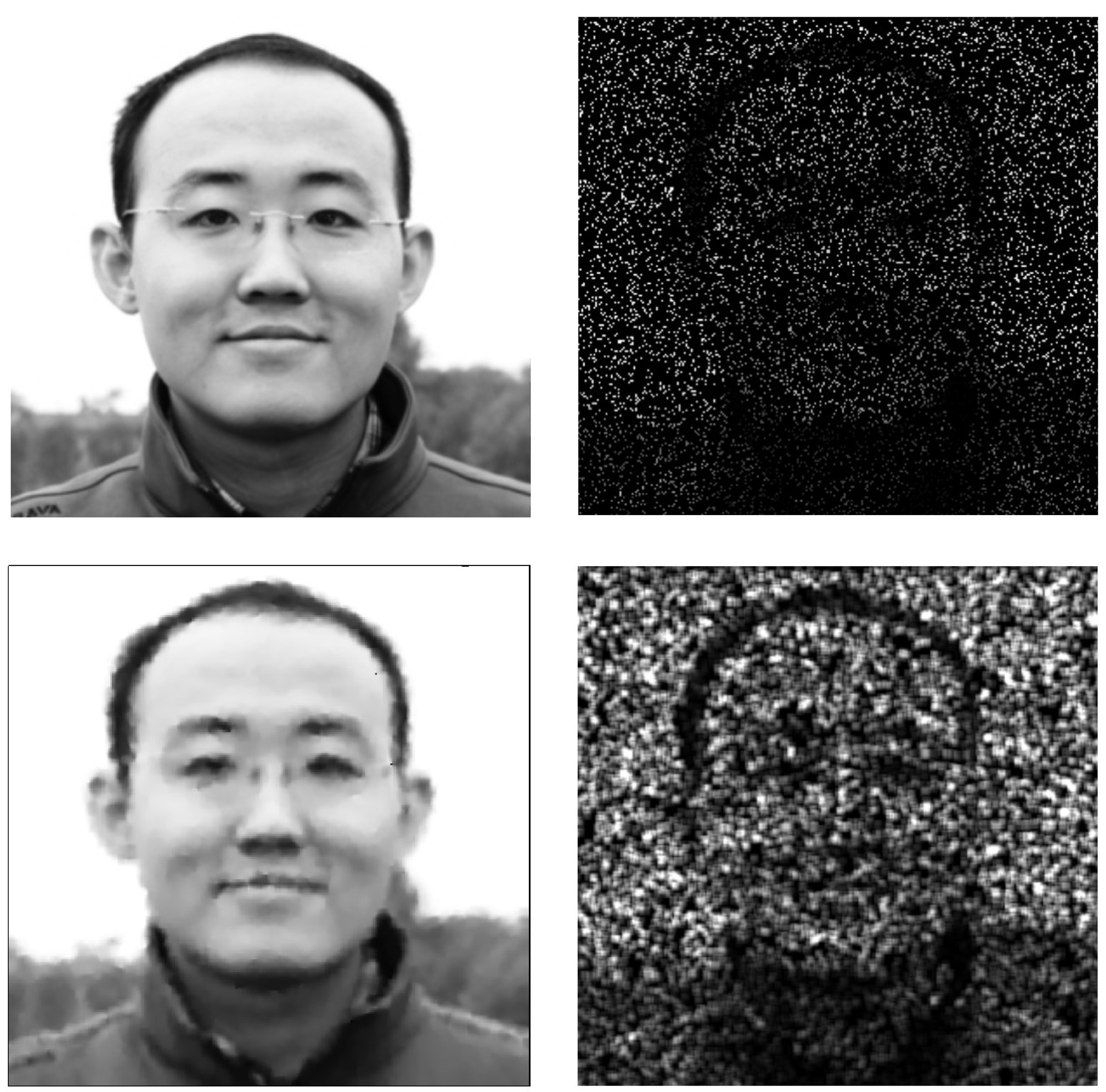

Figure 1: Interpolation of a sparsely, irregularly sampled image using normalized convolution. (Upper Left) photo of the author. (Upper Right) A randomly sampled image containing only 10% pixels of the original image. (Bottom Left) Reconstructed image using normalized convolution (averaging function). (Bottom Right) Reconstructed image using naive low pass filtering.

Synthetic Example

To demonstrate the effectiveness of the method, we apply our normalized convolution filter to synthetic data to test its performance, in the really noisy situation with different sampling rates.

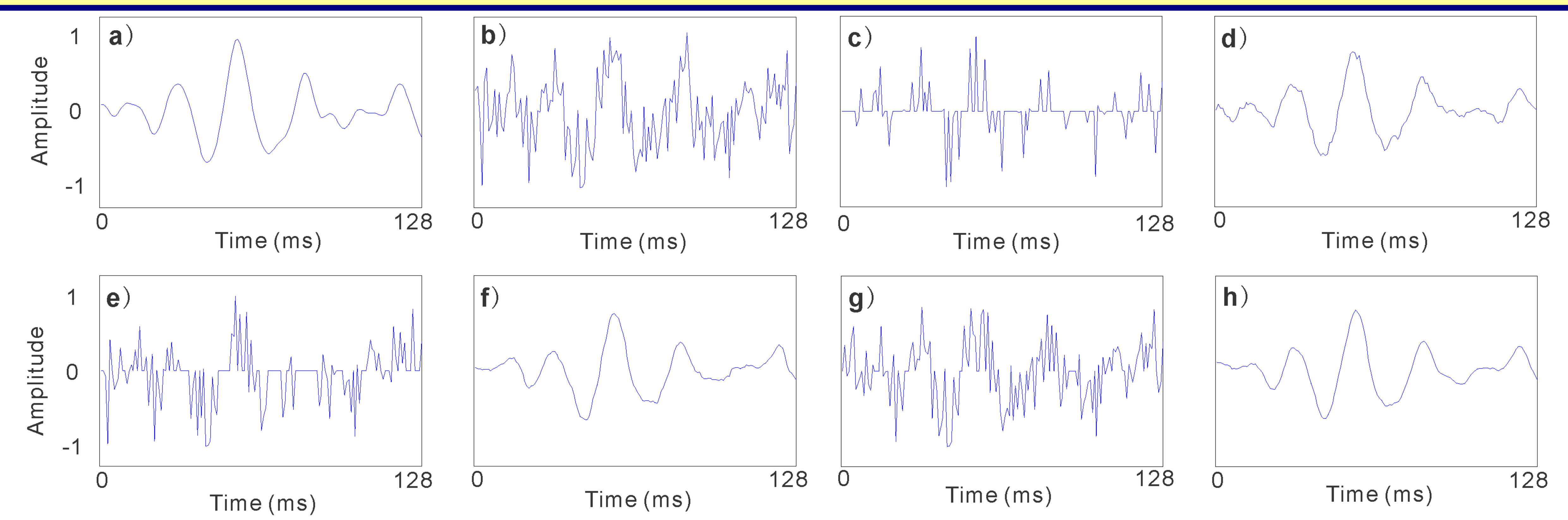

Figure 2: 1D synthetic seismic trace filtering. (a) Noise-free seismic trace. (b) 0 dB noisy trace. (c) 30% randomly sampled data. (d) Reconstructed trace from (c). (e) 50% randomly sampled data. (f) Reconstructed trace from (e). (g) 80% randomly sampled data. (h) Reconstructed trace from (g).

Field Data Example

To test the capability of our approach in the cases of low SNR, we add artificial random noise to the original data. The input data of Figure 3 and Figure 4 are noisy with SNRs of 0 dB and -10 dB, respectively. As the definition of SNR is the common logarithm of the ratio of the power of signal and the power of noise, the noise in Figure 3 is as strong as the input data, while the power of noise is Figure 4 is 3 times of that of signal. Note that the filtered result of the 0 dB noise data very clean, which proves that the proposed method can remove strong noise. In addition, when the noise is 3 times stronger than the input data, we are still able to reconstruct the main features (Figure 4).

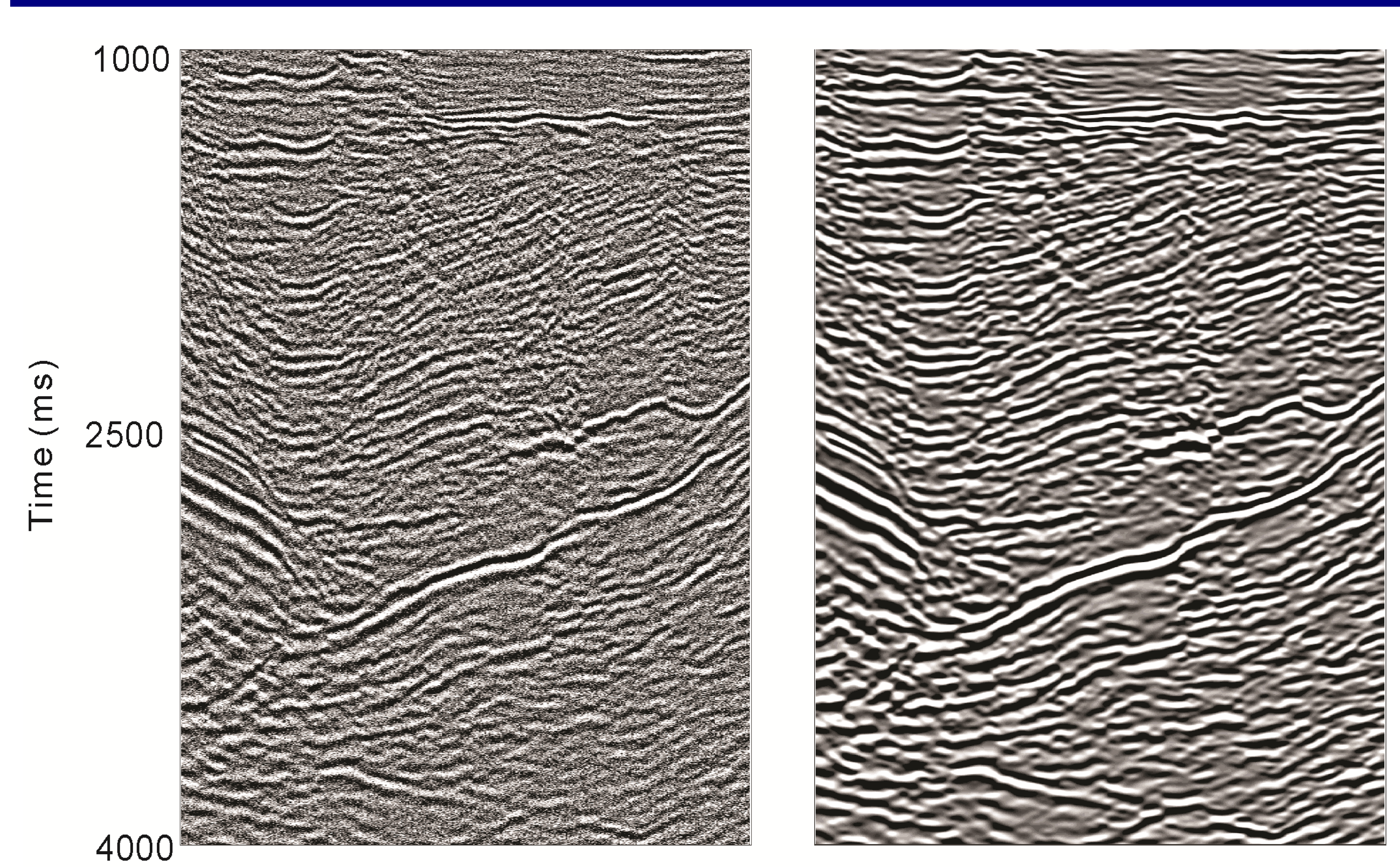

Figure 3: (Left) Seismic section with 0 dB noise on original data. (Right) Filtered result .

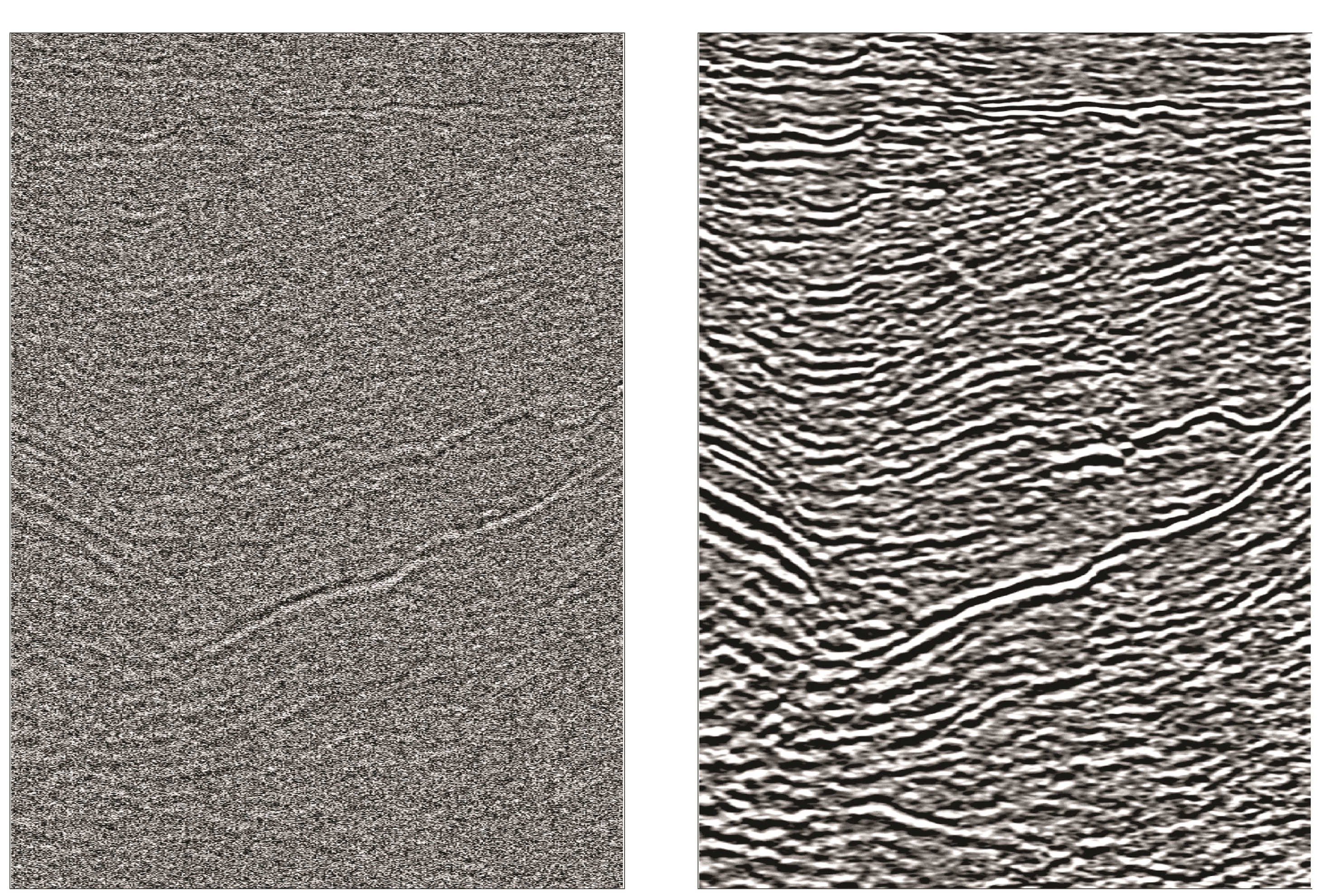

Figure 4: (Left) Seismic section with –10 dB noise on original data. (Right) Filtered result.

Conclusions

We develop a local filtering method based on normalized convolution to attenuate the random noise in seismic data. By testing this approach on synthetic and real data, we demonstrate that the proposed filter has a clear effect on suppressing random noise and can recover seismic events. Comparing the results of input data with different SNR, we find that our approach has wide applicability, especially in the cases of noisy seismic data with low SNR.

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