Noise Suppression via Ensemble Empirical Mode Decomposition

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Summary

Random and coherent noise exist in microseismic and seismic data, and suppressing noise is a crucial step in seismic processing. We propose a novel seismic denoising method, based on ensemble empirical mode decomposition (EEMD) combined with adaptive thresholding. A signal is decomposed into individual components, called intrinsic mode functions (IMF). Each decomposed signal is then compared to those IMFs resulting from a white noise realization to determine if the original signal contains structural features or white noise only. A thresholding scheme then removes all non-structured portions. The proposed scheme is very flexible and applicable in a variety of domains or a diverse set of data. For instance it can serve as an alternative for random noise removal by bandpass filtering in the time domain or spatial prediction filtering in the frequency-offset domain to enhance the lateral coherence of seismic sections. We demonstrate its potential for microseismic and reflection seismic denoising by comparing its performance on field data using a variety of methods including bandpass filtering, basis pursuit denoising, and frequency-offset deconvolution and frequency-offset EMD.

Introduction

The denoising via EMD started from examining the properties of IMFs resulting from white Gaussian noise (Flandrin et al., 2004b). The first attempt is detrending and de-noising ECG signals by partial reconstructions with the selected IMFs (Flandrin et al., 2004a). However, this approach has the disadvantage that even if the appropriate IMFs are selected, they still may be noise contaminated. Boudraa and Cexus (2006) improve the denoising scheme by using adaptive thresholding and a Savitzky-Golay filter for each IMF, respectively. Inspired by translation invariant wavelet thresholding, Kopsinis and McLaughlin (2009) propose an iterative EMD denoising method to enhance the original method. In seismic processing, Bekara and Van der Baan (2009) first apply of EMD in f-x (frequency-offset) domain, as f-x EMD. They find that eliminating the first IMF component in each frequency slice corresponds to an auto-adaptive wavenumber filter, thus reducing the random and steeply dipping coherent noise in the seismic data.

In this paper, we first propose a novel method for suppressing random noise based on ensemble empirical mode decomposition (EEMD) principle. Next, we test the proposed EEMD thresholding on microseismic example. Finally, we extend the proposed method into the f-x domain to suppress random and coherence noise in seismic data.

Theory

The first attempt at using EMD as a denoising tool emerged from the need to know whether a specific IMF contains useful information or primarily noise. Thus, Flandrin et al. (2004b) and Wu and Huang (2004) nearly simultaneously investigate the EMD feature for Gaussian noise, and they conclude that EMD acts essentially as a dyadic filter bank resembling those involved in wavelet decomposition. Therefore, the energy of each IMF from white Gaussian noise follows an exponential relationship, and Kopsinis and McLaughlin (2009) refine this relationship as

$$E_k^2 = E_1^2 / 0.719 * 2.01^{-k}, \tag{1}$$

where E_k^2 is the energy of the *k-th* IMF, and the parameters 0.719 and 2.01 are empirically calculated from numerical tests. As the IMFs resemble the wavelet decomposition component, the energy of the first IMF E_1^2 can be estimated using a robust estimator based on the component's median (Donoho and Johnstone, 1994; Herrera et al., 2014):

$$E_1^2 = (\text{median}(|IMF_1(\text{i})|) / 0.6755)^2, \quad i = 1, 2...n. \tag{2}$$

where *n* is the length of the input signal. Then we can set the adaptive threshold T_k in each IMF for suppressing the random noise as

$$T_k = \sigma * \sqrt{2 * \ln(\text{n})} * E_k, \tag{3}$$

where σ is the main parameter to be set. Combination of Equations 2 and 3 is a universal threshold for removing the white Gaussian noise in the wavelet domain. Followed by the above procedures, the reconstructed signal $\hat{s}$ is expressed as

$$\hat{s} = \sum_{k=m1}^{M-m2} T_k[\text{IMF}_k] + \sum_{k=m2+1}^{M} IMF_k, \tag{4}$$

thresholding is only applied between the *m1-th* and *m2-th* IMFs, where IMF_k is the *k-th* IMF, and *M* is the total number of IMFs of the input signal. If *m*2 is set to 0, we apply the thresholding from the *m1-th* IMF to the last IMF. The implemented threshold method is IMF interval thresholding (Kopsinis and McLaughlin, 2009).

Due to the mode mixing of EMD, direct application of the above procedure may not achieve the best effect. Considering the different SNR cases, we employ the EEMD principle to improve the EMD denoising performance. The procedure of EEMD denoising is as below:
(1). Create white Gaussian noise.
(2). Calculate IMF1 of the white Gaussian noise and add it onto the target signal using a predefined SNR.
(3). Decompose the resulting signal into IMFs.
(4). Apply the EMD denoising principle to the resulting IMFs.
(5). Repeat steps (1), (2), (3) and (4) several times with different noise realizations.
(6). Compute the ensemble denoising average as the final output.

Although not adding the whole white Gaussian noise sequence onto the target signal does not exactly respect the EEMD principle, it shows better results in our test data examples rather than a denoising procedure exactly based on EEMD. Due to the dyadic filter feature of EMD, IMF1 of white Gaussian noise corresponds to the high frequency noise. It helps relieve the mode mixing of EMD to some extent, and only affects the high frequency information of the input signal, which can be compensated by a bandpass filter after the proposed EEMD denoising.

Examples

The first example is a challenging microseismic event (Castellanos and van der Baan, 2013) is shown in Figure 1, which comes from Saskatchewan in Canada. The raw data (Figure 1(a)) quality is bad, as it does not only contain random noise, but also strong electronic noise. High energy 30 Hz, 60Hz and 120 Hz noise components exist in its spectra (Figure 2(a)). Directly applying the EEMD thresholding and basis pursuit to the raw data would fail, as they are only valid for suppressing random noise. A pre-processing step must be accomplished before the further processing. Figure 1(b) is the output after a bandpass filter and notch process of 30 Hz and 60 Hz. The 120 Hz energy is not notched down as it is not visible in the other microseismic events of this experiment.

Even though the pre-processing improves the quality of the raw data, Figure 1(b) still suffers from severe random noise. EEMD thresholding (Figure1(c)) with σ =0.25, *m*1=1 and *m*2=1 reduces more random noise than basis pursuit (Figure 1(d)), and it more effectively (Figure 2(c)) decreases the 120 Hz energy

than basis pursuit (Figure 2(d)). Figure 2 shows the corresponding spectra of Figure 1. Note that the regularization parameter is 35 for the basis pursuit implementation.
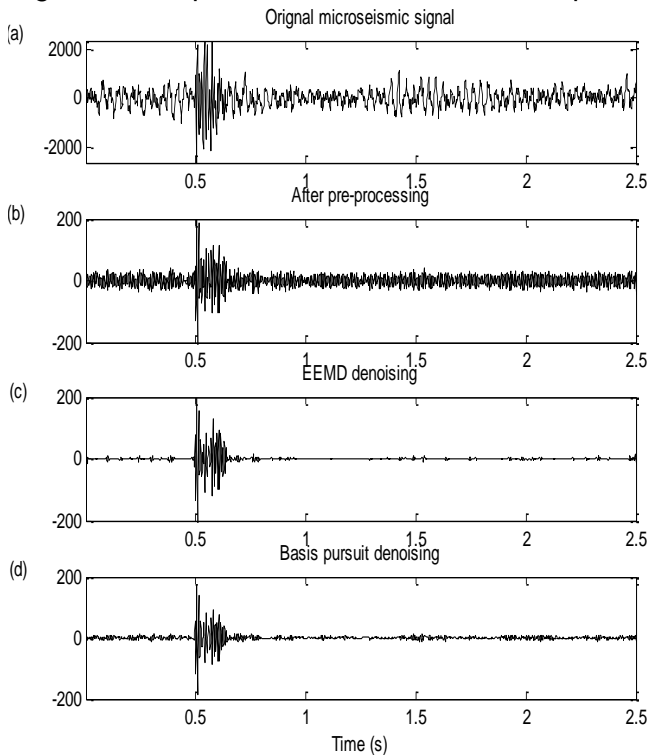

Figure 1: (a). Raw microseismic event. (b). Output after pre-processing. (c). EEMD thresholding output on (b). (d). Basis pursuit output on (b). The raw microseismic event contains random and electronic noise.
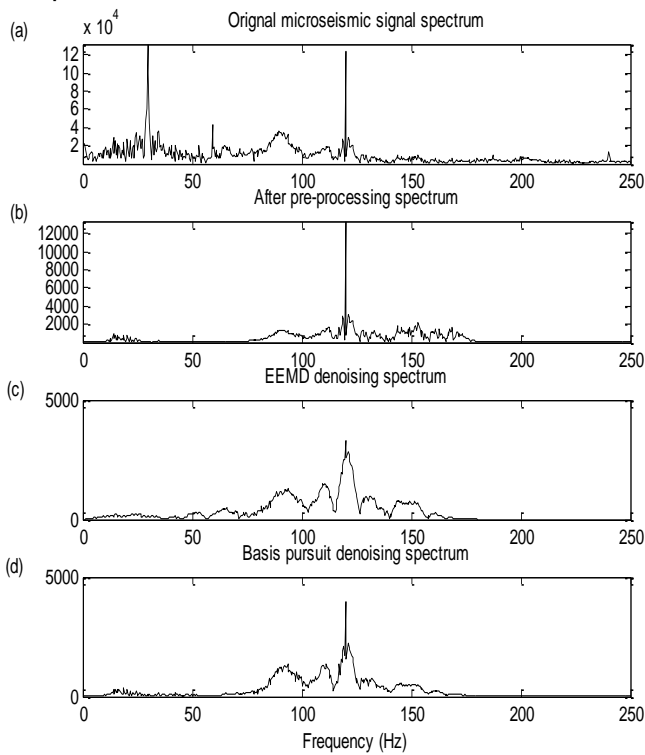
Figure 2: The spectra of Figure 1. (a). Spectra of the raw microseismic event. (b). Spectra after pre-processing. (c). Spectra after the proposed method on (b). (d). Spectra after basis pursuit on (b).
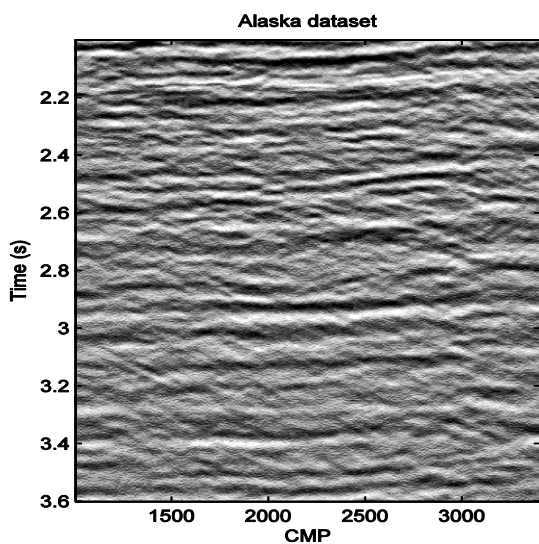

Figure 3: A section of Alaskan data. Courtesy: USGS.

For 2D and 3D seismic data, one option is applying the proposed EEMD thresholding for each trace to suppress the random noise; Yet with the disadvantage that this approach does not consider the lateral coherence of seismic reflections. A more sophisticated approach is to apply EEMD thresholding in the f-x domain. Figure 3 is a section of Alaskan data. It clearly shows that these data do not only contain random but also coherent noise, like high energy linear dipping events. The same sections after three different denoising outputs are shown in Figure 4. F-x EEMD thresholding (Figure 4(c)) obtains the most satisfactory output, and the events become much clearer.

There are still some random and coherent noise in the results of f-x EMD (Figure 4(a)) and f-x deconvolution (Figure 4(b)) in varying degrees. F-x EMD, which eliminates only the first IMF component in each frequency slice, does not seem to have great impact on the data. The proposed method uses parameters $m1 = 3$, $m2 = 0$ and $\sigma = 0.3$ which deletes the first two IMFs, and then applies

the IMF interval thresholding from IMF3 to the last IMF. EMD thresholding thus removes both random and dipping results as seen in the difference section (Figure 5(c)), whereas f-x EMD eliminates merely the random noise (Figure 5(a)), but f-x deconvolution is only valid for random noise suppression; no dipping noise is shown in its difference profile (Figure 5(b)).

Conclusions

EEMD thresholding distinguishes between structured signal and random noise within each IMF. It can serve as an alternative to simple bandpass filtering with the advantage that it acts as a nonstationary (time-varying), auto-adaptive, frequency filter. In this sense it performs equally well or possibly even better than basis pursuit denoising. If applied in the f-x domain, the method acts as a sophisticated wavenumber filter, removing both random and dipping coherent noise. The microseismic and reflection seismic examples illustrate the good performance of the proposed method.
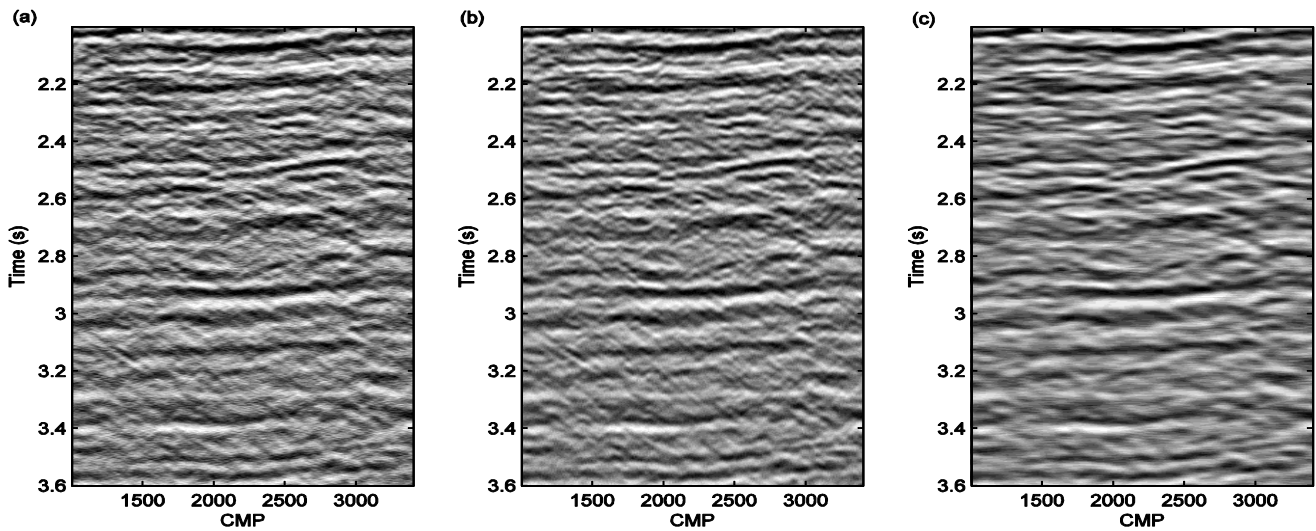
Acknowledgements

Figure 4: (a). Result of f-x EMD. (b). Result of f-x deconvolution. (c). Result of the proposed method.
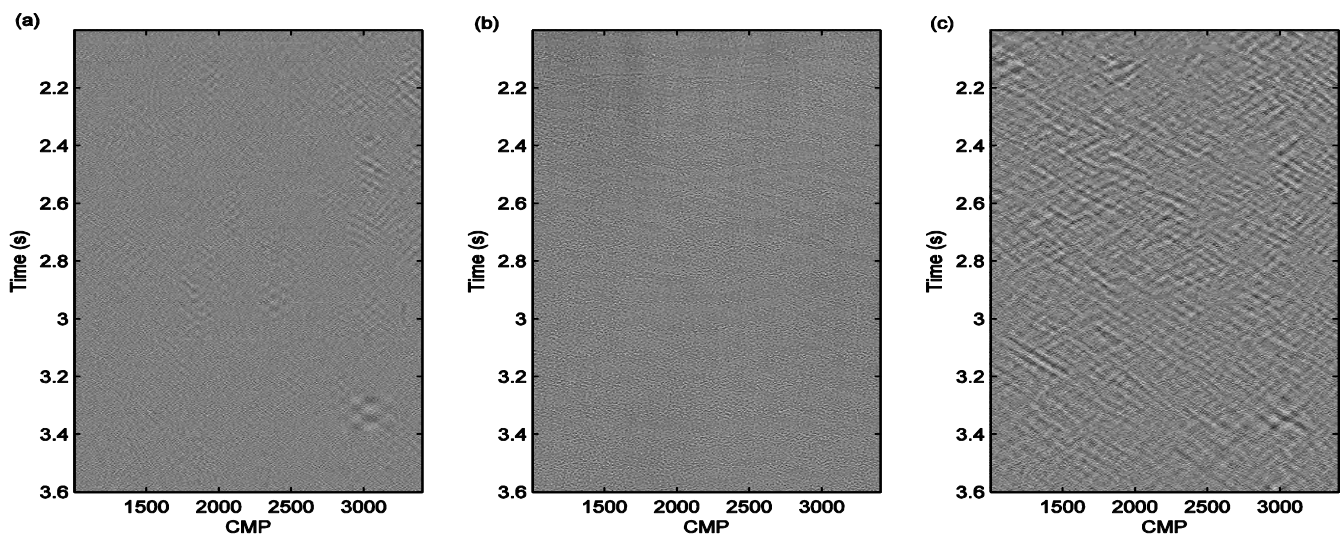

Figure 5: (a). Difference section of f-x EMD. (b). Difference section of f-x deconvolution. (c). Difference section of the proposed method.

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