Seismic denoising using VMD

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Summary

Noise reduction is critical for structural, stratigraphic, lithological and quantitative interpretation. In the absence of physical insight into its cause and behavior, separating the noise from the underlying signal can be difficult. We construct a noise suppression workflow based on a data-adaptive signal decomposition method (variational mode decomposition). Key to our workflow is to determine which of the generated intrinsic mode functions represent signal and which represent noise. We address this issue by a scaling exponent based on detrended fluctuation analysis. The proposed method shows excellent performance on synthetic and field data, especially when encountering data exhibiting a low signal-to-noise ratio. Laterally continuous events are preserved and steeply dipping coherent events due to aliasing as well as random noise are rejected.

Introduction

Seismic signal is non-stationary because of the complex subsurface structures, random and coherent interferences, as well as acquisition related noises. Denoising is a necessary step to enhance signal-to-noise ratio (SNR). Methods based on signal decomposition and thresholding scheme show good performance in denoising non-stationary signal (Donoho and Johnstone, 1994; Chkeir et al., 2010).

Empirical mode decomposition (EMD) analyzes non-stationary signals and adaptively decomposes signal into oscillatory components called intrinsic mode functions (IMF) plus a residual. However, EMD has the frequency mixing issue, especially in low SNR situation (Kabir and Shahnaz, 2012).

Variational mode decomposition (VMD) decomposes a signal into an ensemble of band-limited IMFs (Dragomiretskiy and Zosso, 2014). VMD solves an optimization problem in frequency domain to best isolate different spectral modes.

Working on the adaptively decomposed signal components, EMD and VMD based denoising methods require a criterion to separate noise from the signal. Theoretically, the decomposed IMFs carry most of the signal components whereas the majority of the noise components and some of the mode components would be left as residual. Peng et al. (1994) proposed detrended fluctuation analysis (DFA) to analyze different trends of unknown duration. The scaling exponent estimated from DFA is used to evaluate the variation of the average root mean square (RMS) fluctuation around the local trend. Moreover, the scaling exponent value is also an indicator of roughness: the larger value, the smoother time series or slower fluctuations (Horvatic et al., 2011; Berthouze and Farmer, 2012).

Method

Essentially, EMD is a sifting process. Thus, the original signal can be reconstructed by the IMF components with the following representation:

$$s(t)=\sum_{k=1}^{K} IMF_k(t)+r_K(t)$$

Where, IMF_k is the kth IMF of the signal, and r_k stands for the residual trend. In EMD, low order IMFs represent fast oscillations (high-frequency modes), and high order IMFs represent slow oscillations (low-frequency modes).

VMD decomposes intrinsic modes in the frequency domain, which are compact around their respective central frequencies. In VMD, the IMFs are defined as elementary amplitude/frequency modulated (AM-FM) harmonics to model the non-stationarity of the data. In other words, for a sufficiently long interval, the mode can be considered to be a pure harmonic signal. The VMD is realized by solving the following optimization problem:

$$\min_{\{u_k,\ \omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t)+\frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}$$
$$s.\ t. \quad \sum_k u_k = d(t)$$

where u_k and ω_k are modes and central frequencies, respectively. $\delta(\bullet)$ is a Dirac impulse. *d(t)* is the signal to be decomposed, with the constraint that the summation over all modes should be the input signal. $\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)$ is the Hilbert transform.

DFA estimates signal nonstationary properties based on its scaling exponent. If the data (length N) are long-range power-law correlated, the RMS fluctuation around the local trend in the box size n increases following a power law:

$$F(n)=\sqrt{\frac{1}{N}\sum_{k=1}^{K}\left[y(k)-y_n(k)\right]^2} \qquad \propto \qquad n^{\alpha}$$

where the scaling exponent a is defined as the slope of the curve *[F(n)]/log(n)* , which is estimated as the log-log scale Hurst exponent. y(k) is the time series subtracted from the mean value. $y_n(k)$ is the estimated local trend by simply fitting a linear line. When $0 < \alpha < 0.5$, the signal is anti-correlated. When $\alpha = 0.5$, it corresponds to uncorrelated white noise (Mert and Akan, 2014).

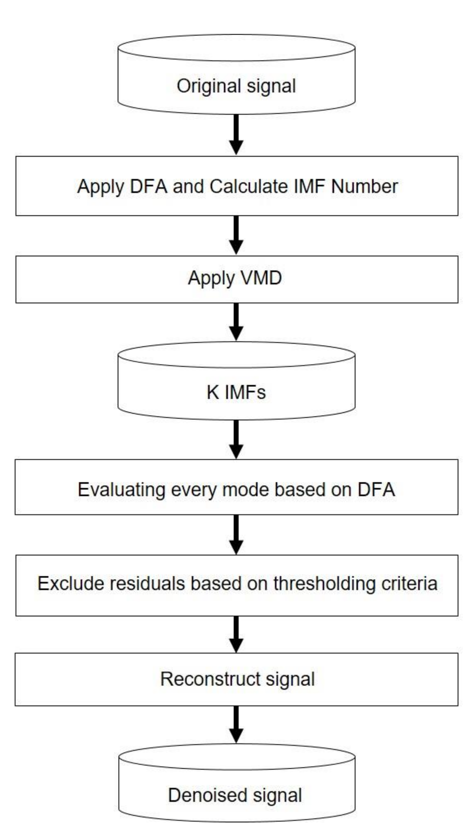

Fig 1: Denoising workflow

Synthetic Examples

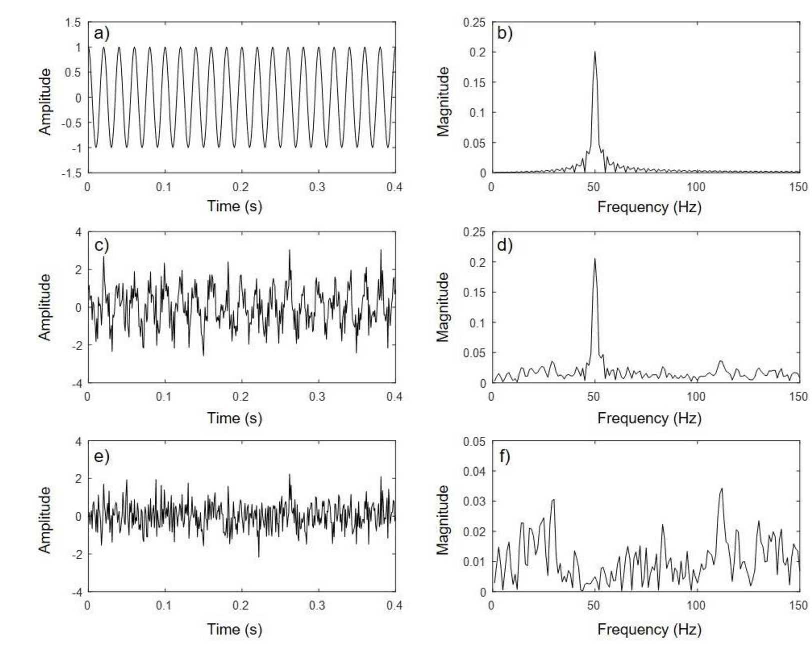

Fig 2: Noisy signal synthetic example: (a) 50 Hz noise free signal with its spectrum (b); (c) 3 dB noisy signal with its spectrum (d); (e) the added noise and the noises spectrum (f).

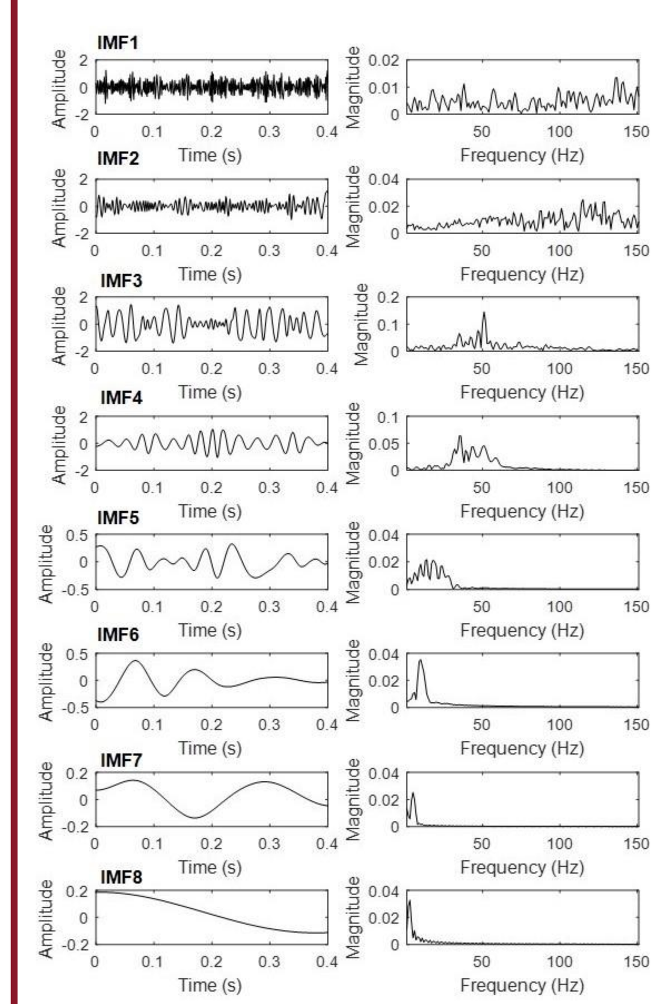

Fig 3: EMD decomposition results.

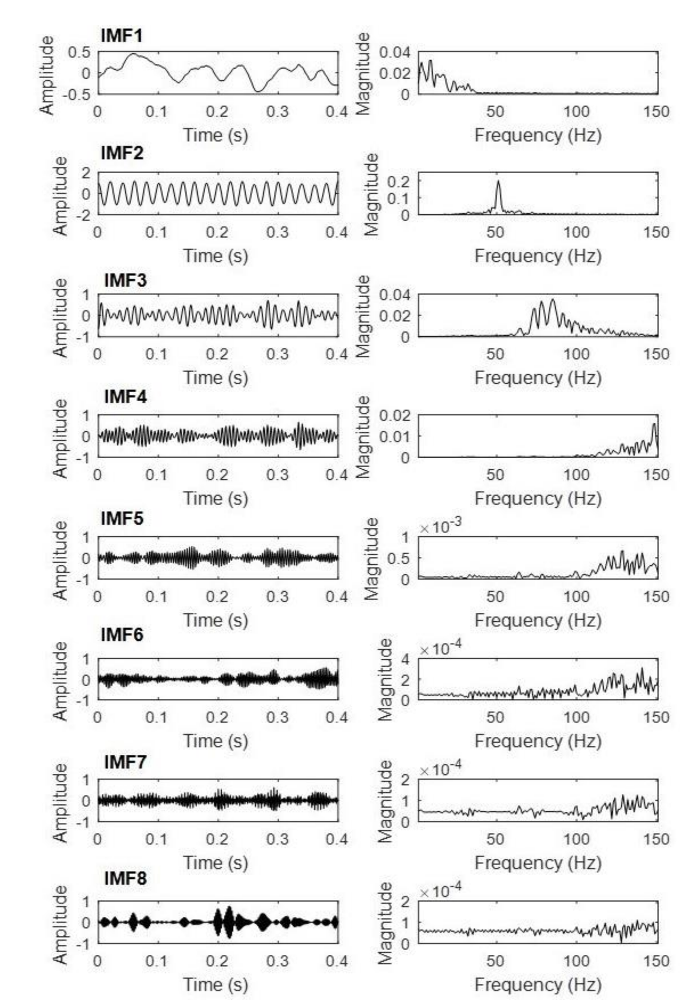

Fig 4: VMD decomposition results.

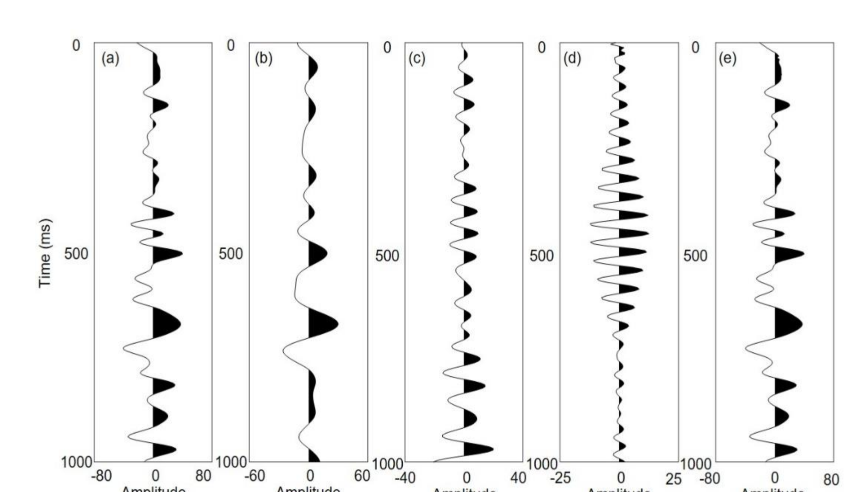

Fig 5: Seismic trace (a) and IMFs from VMD (b-d). The reconstructed signal is shown in (e).

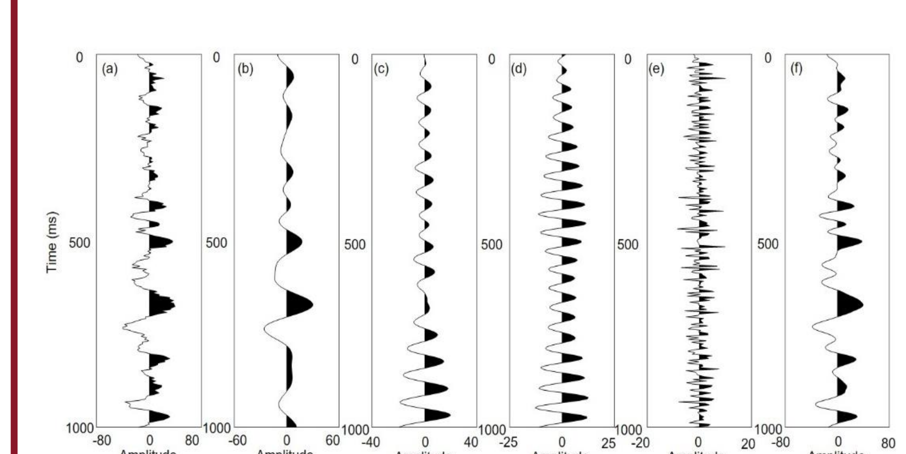

Fig 6: Noisy seismic trace with 10dB additional noise (a) and IMFs from VMD (b-d). The residual between the noisy signal and summation of IMFs is displayed in (e). The reconstructed signal is shown in (f).

Field Applications

We apply the proposed workflow to a low fold, land seismic survey acquired in the mid-1990s that suffers from backscattered ground roll and migration operator aliasing. This data set is from North Central Texas, where the target is discontinuous high porosity Mississippian Chert (Verma et al., 2016).

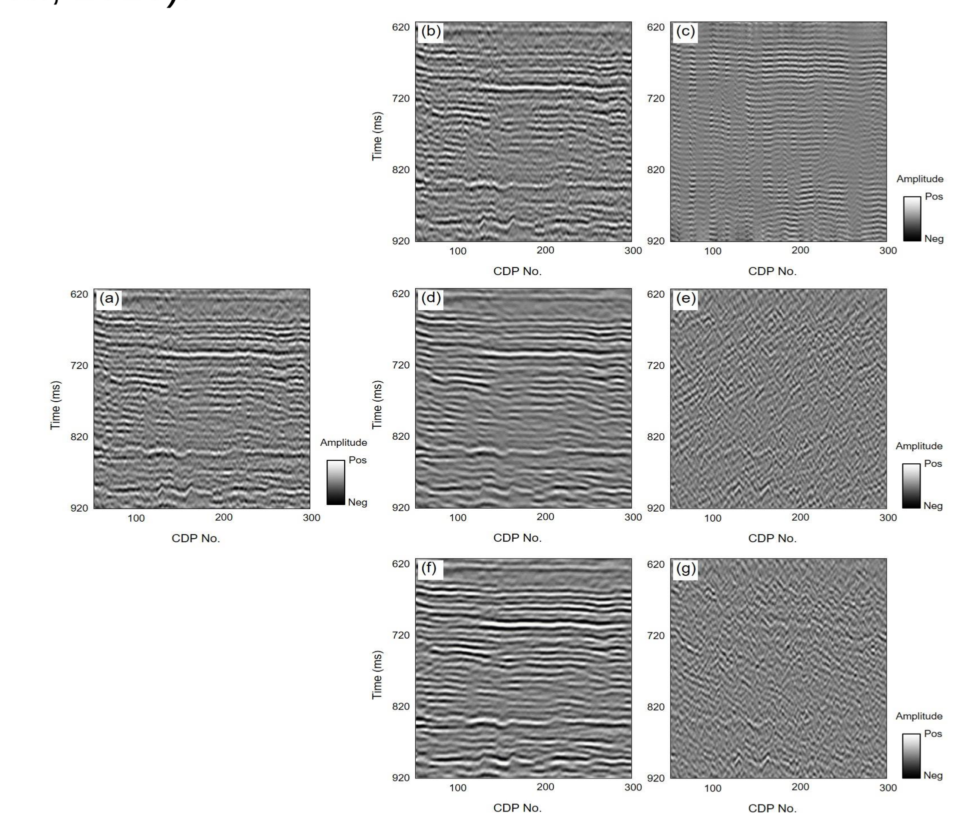

Fig 7: Vertical sections with flat events through (a) noisy seismic data, (b) filtered result from a bandpass filter (0-10-60-70 Hz) and (c) difference between (a) and (b). (d) Filtered result from EMD and (e) difference between (a) and (d). (f) Filtered result from VMD and (g) difference between (a) and (f).

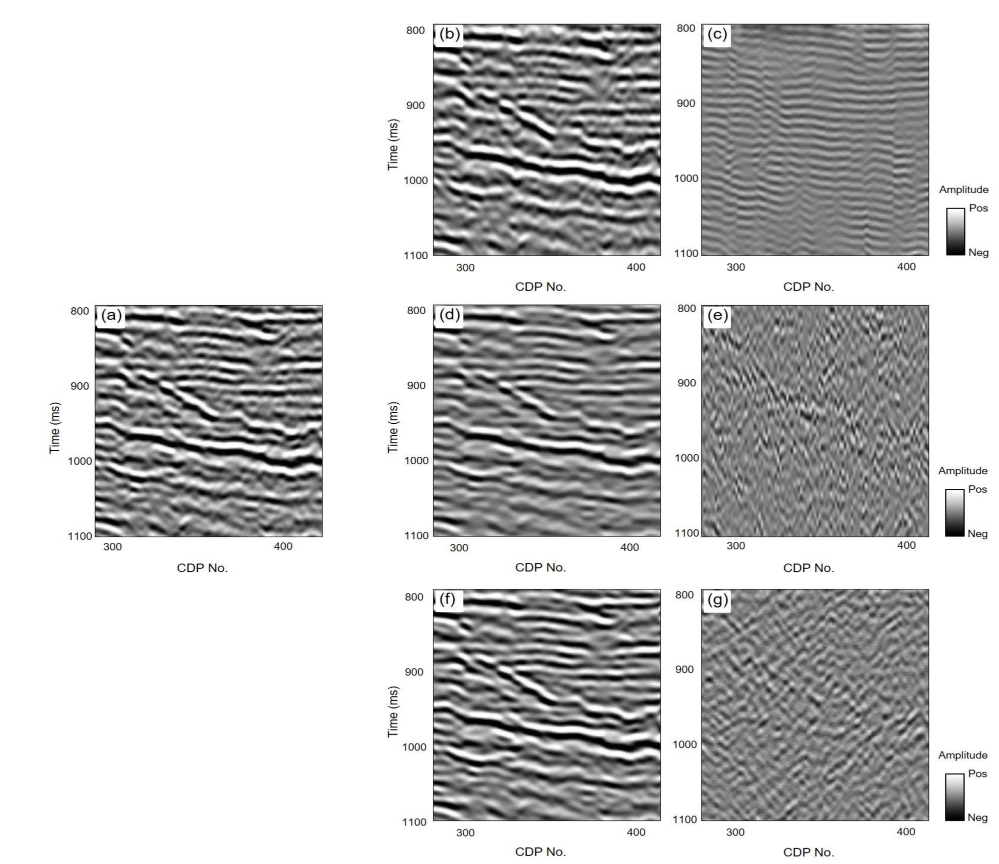

Fig 8: Vertical sections with dipping events through (a) noisy seismic data, (b) filtered result from a bandpass filter (0-10-60-70 Hz) and (c) difference between (a) and (b). (d) Filtered result from EMD and (e) difference between (a) and (d). (f) Filtered result from VMD and (g) difference between (a) and (f).

Conclusions

We propose a DFA thresholding for VMD based denoising method. A few IMFs of a noisy measured data can represent signal, while the residuals represent noise. To achieve this objective, we use exponents from DFA as a metric to determine which IMFs are noisy oscillations and should be excluded in the reconstruction process. Synthetic and field examples demonstrate that our method is promising.

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