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Seismic Time-Frequency analysis by Empirical Mode Decomposition

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Summary

Time frequency analysis plays a significant role in seismic data processing and interpretation. Complete ensemble empirical mode decomposition (CEEMD) decomposes a seismic signal into a sum of oscillatory components, with guaranteed positive and smoothly varying instantaneous frequencies. Analysis on real data demonstrates that this method promises higher spectral-spatial resolution than the short-time Fourier transform. Application on field data thus offers the potential of highlighting subtle geologic structures that might otherwise escape unnoticed.

Introduction

The empirical mode decomposition (EMD) method developed by Huang et al. (1998) is a powerful signal analysis technique for non-stationary and nonlinear systems. EMD decomposes a seismic signal into a sum of intrinsic oscillatory components, called Intrinsic Mode Functions (IMFs). Each IMF has different frequency components, potentially highlighting different geologic and stratigraphic information. Furthermore, high-resolution time-frequency analysis is possible by combining EMD with the instantaneous frequency. The resulting time-frequency resolution promises to be significantly higher than that obtained using traditional time-frequency analysis tools, such as short time Fourier and wavelet transforms.

The empirical mode decomposition methods have progressed from EMD to ensemble empirical mode decomposition (EEMD) (Wu and Huang, 2009), and recently a complete ensemble empirical mode decomposition (CEEMD) has been proposed by Torres et al. (2011). Even though EMD methods offer many promising features for analyzing and processing geophysical data, there have been few applications in geophysics. Magrin-Chagnolleau and Baraniuk (1999) and Han and Van der Baan (2011) use EMD to obtain robust seismic attributes. Battista et al. (2007) exploit EMD to remove cable strum noise in seismic data. Bekara and Van der Baan (2009) eliminate the first EMD component in the f-x domain to attenuate random and coherent seismic noise. Huang and Milkereit (2009) utilize the EEMD to analyze the time frequency distribution of well logs. Han and van der Baan (2013) combine the instantaneous spectrum with CEEMD for seismic time frequency analysis.

Complete ensemble empirical mode decomposition (CEEMD)

CEEMD is a noise-assisted method. The procedure of CEEMD can be described as follows (Torres et al., 2011):

First, add a fixed percentage of Gaussian white noise onto the target signal, and obtain the first EMD component of the data with noise. Repeat the decomposition I times using different noise realizations and compute the ensemble average to define it as the first IMF_1 of the target signal. Thus,

$$IMF_1 = \frac{1}{I}\sum_{i=1}^{I} E_1[x + \varepsilon w_i] \,. \quad (1)$$

where IMF_1 is the first EMD component of the target signal x, w_i is zero-mean Gaussian white noise with unit variance, ε is a fixed coefficient, $E_i[]$ produces the $i-th$ IMF component and I is the number of realizations.

Then calculate the first signal residue r_1,

$$r_1 = x - IMF_1. \tag{2}$$

Next decompose realizations $r_1 + \varepsilon E_1[w_i], \quad i = 1,2,...,I$, until they reach their first IMF conditions and define the ensemble average as the second IMF_2:

$$IMF_2 = \frac{1}{I}\sum_{i=1}^{I} E_1[r_1 + \varepsilon E_1[w_i]] . \tag{3}$$

For $k = 2,3,...,K$ calculate the $k-th$ residue: $r_k = r_{(k-1)} - IMF_k$, then extract the first IMF component of $r_k + \varepsilon E_k[w_i], \quad i = 1,2,...,I$ and compute again their ensemble average to obtain $IMF_{(k+1)}$ of the target signal:

$$IMF_{(k+1)} = \frac{1}{I}\sum_{i=1}^{I} E_1[r_k + \varepsilon E_k[w_i]] . \tag{4}$$

The sifting process is continued until the last residue does not have more than two extrema, producing,

$$R = x - \sum_{k=1}^{K} IMF_k \ . \tag{5}$$

where R is the final residual, and K is the total number of IMFs. Therefore the target signal can then be expressed as:

$$x = \sum_{k=1}^{K} IMF_k + R \ . \tag{6}$$

Equation (6) makes CEEMD a complete decomposition method (Torres et al., 2011). Compared with both EMD and EEMD, CEEMD not only solves the mode mixing predicament, but also provides an exact reconstruction of the original signal. Therefore, it is more suitable than EMD or EEMD to analyze seismic signals (Han and van der Baan, 2013).

Instantaneous frequency

The local symmetry property of the IMFs ensures that instantaneous frequencies are always positive, thereby rendering EMD or its variants interesting for time-frequency analysis. Seismic instantaneous amplitude $R(t)$ and instantaneous frequency $f(t)$ (Taner et al., 1979) are derived from the seismic trace $x(t)$ and its Hilbert transform $y(t)$ by computing its analytic signal, given by,

$$R(t) = \sqrt{x^2(t) + y^2(t)}. \tag{7}$$

$$f(t) = \frac{1}{2\pi}\frac{x(t)y'(t) - x'(t)y(t)}{x^2(t) + y^2(t)} . \tag{8}$$

where prime denotes derivative with respect to time.

We use equations (7) and (8) to compute instantaneous amplitudes and frequencies for each IMF and create the instantaneous spectrum.

Real data example

We perform a spectral decomposition of a 3D seismic data volume using CEEMD and compare with the short time Fourier transform. Figure 1 shows a time slice displaying both the channel feature, as well as a subtle fault. CEEMD employs 10% added Gaussian white noise and 50 realizations. A window length of 150ms (75 points) is used for the short time Fourier transform, producing a frequency step of 7 Hz in the spectral decomposition.

Figures 2a and 2c show respectively the 10Hz and 30Hz spectral slices for the instantaneous spectrum after CEEMD. Both the channel and fault are visible, especially at 30Hz. Both spectral slices show similar features; yet there are also clear differences, in particular in the amplitudes of the channel, indicating little spectral leakage across these two frequencies. These amplitude differences are helpful in interpreting thickness variations.

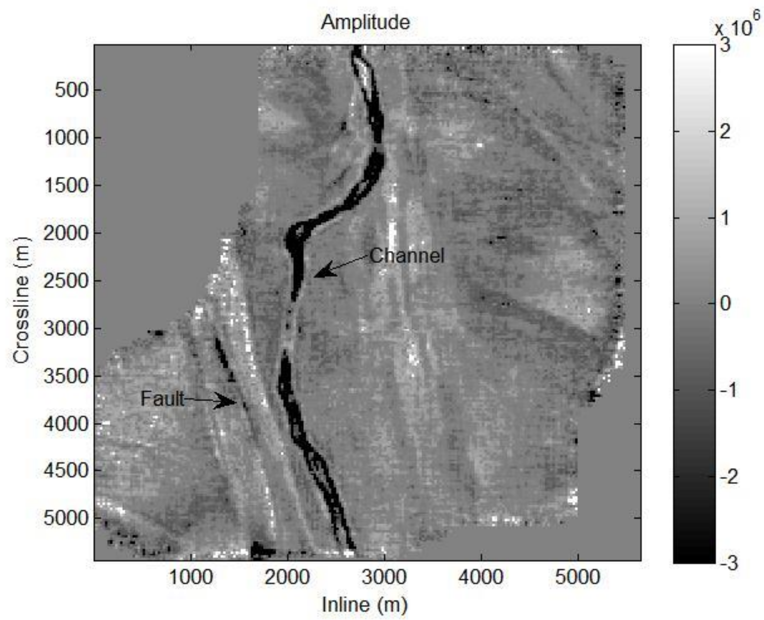

Figure 1: The conventional amplitude slice. The channel feature is clearly shown.

The 10 and 30Hz spectral slices produced by Fourier analysis also show the fault and channel features (Figures 2b and 2d). However, there are significantly less amplitude variations across both slices as unique frequencies are spaced 7Hz apart due to the short window length and the spectral leakage inherent to the Fourier transform. This renders interpretation of thickness variations in the channel much more challenging as thinning or thickening by a factor two may still produce the same amplitudes across several spectral slices centered on the expected peak frequency. We could have opted for a longer Fourier analysis window, thereby reducing the frequency step in the amplitude spectra. On the other hand, this increases the risk of neighboring reflections negatively biasing the decomposition results. No local analysis window is defined for the CEEMD method thus circumventing this trade off.

Conclusions

CEEMD is a robust extension of EMD methods. It solves not only the mode mixing problem, but also leads to complete signal reconstructions. After CEEMD, instantaneous frequency spectrum manifest visibly higher time-frequency resolution than short time Fourier transform on field data example. These characteristics render the technique highly promising for both seismic processing and interpretation.

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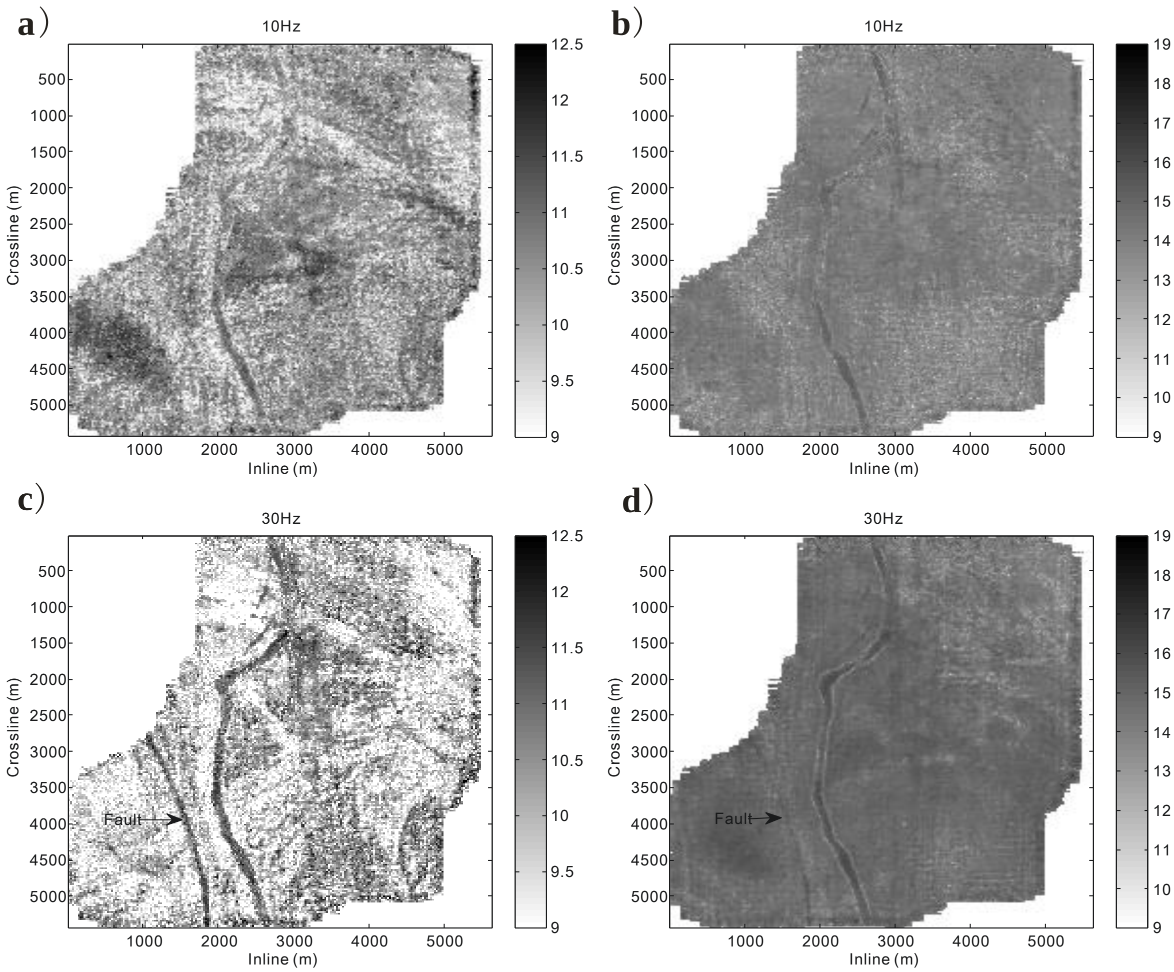

Figure 2: Comparison of time slices: a) 10Hz of CEEMD-based method; b) 10Hz of short time Fourier transform; c) 30Hz of CEEMD-based method; d) 30Hz of short time Fourier transform. CEEMD-based method highlights the geologic features more clearly and facilitates the interpretation of thickness variation.

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