Journal of Applied Geophysics 111 (2014) 102–109

Contents lists available at ScienceDirect

Journal of Applied Geophysics

journal homepage: www.elsevier.com/locate/jappgeo

A robust method for analyzing the instantaneous attributes of seismic data: The instantaneous frequency estimation based on ensemble empirical mode decomposition

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ARTICLE INFO

Article history:
Received 10 June 2014
Accepted 25 September 2014
Available online 2 October 2014

Keywords:
Ensemble empirical mode decomposition
Instantaneous frequency
Mode mixing
The thickness of stratum

ABSTRACT

The Hilbert–Huang transform (HHT) includes two procedures. First, empirical mode decomposition (EMD) is used to decompose signals into several intrinsic mode functions (IMFs) before the Hilbert transform (HT) of these IMFs are calculated. Compared to the conventional Hilbert transform (HT), HHT is more sensitive to thickness variations of seismic beds. However, random noise in seismic signal may cause the mixture of the modes from HHT. The recent ensemble empirical mode decomposition (EEMD) presents the advantages in decreasing mode mixture and has the promising potential in seismic signal analysis. Currently, EEMD is mainly used in seismic spectral decomposition and noise attenuation. We extend the application of EEMD based instantaneous frequency to the analysis of bed thickness. The tests on complex Marmousi2 model and a 2D field data show that EEMD is more effective in weakening mode mixtures contained in the IMFs, compared with that calculated by EMD. Furthermore, the EEMD based instantaneous frequency is more sensitive to the seismic thickness variation than that based on EMD and more consistent with the stratigraphic structure, which means that E-IFPs are more advantageous in characterizing reservoirs.

1. Introduction

The instantaneous attributes extracted from seismic data, especially the instantaneous frequency (noted as IFP), are generally used in seismic stratigraphic interpretation, including structure, lithology, thickness of stratum medium and so on. The most common method to estimate the instantaneous attributes is based on Hilbert transform presented by Taner et al. (1979). Instantaneous frequency based on Hilbert transform can be applied only on signals with special monocomponent because it is mathematically defined as the derivative of phase with respect to time (Boashash, 1992; Cohen, 1995). However, seismic signals are nonlinear and non-stationary generally, which may lead to the lack of physical significance of the instantaneous frequency estimated by Hilbert transform. Taking the physical implementations and a local restriction condition definition on the signals into account, empirical mode decomposition (EMD) and Hilbert–Huang transform (HHT) are proposed (Huang et al., 1998). Firstly, EMD is utilized to decompose a signal into a series of intrinsic mode functions (IMFs) that meet the requirement in estimating instantaneous frequency by Hilbert transform and then Hilbert transform is performed on these IMFs. It is proved that HHT is more applicable to nonlinear and non-stationary signals. Currently the application of EMD in signal processing is mainly utilized in noise attenuation (Bekara and van der Baan, 2009; Chang, 2010), EMD as a filter bank (Flandrin et al., 2004) and so on. In seismic exploration, EMD and Hilbert–Huang transform (HHT) are adopted to estimate instantaneous frequency and time-frequency attributes of seismic data (Han and van der Baan, 2011; Magrin-Chagnolleau and Baraniuk, 1999; Zhou et al., 2012). The published examples have demonstrated their effectiveness. However, one of the major drawbacks of EMD is the mode mixing problem (Wu and Huang, 2009), which means that either a single IMF consists of signals in widely disparate scales, or very similar oscillations reside in different IMF components. This phenomenon is usually the consequence of signal intermittency (Wu and Huang, 2009). The decomposition process in EMD shows that mode mixing is related to the sifting process that is used to obtain the mean of the envelope. The extraction of the envelope depends on the extreme points of target signals and their distribution. If the signal is intermittent, the value of extreme points is a catastrophe and their distribution is abnormal. To guarantee the smoothness of envelope, the envelope is inevitably distorted because of interpolation, causing the envelope to overshoot or undershoot at the signal intermittency and that mode mixing exists in obtained IMFs.

Aiming at the mode mixing, ensemble empirical mode decomposition (EEMD) was proposed (Wu and Huang, 2009), where the final

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http://dx.doi.org/10.1016/j.jappgeo.2014.09.017
0926-9851/

IMF components are defined as the mean of all the ensemble trials. Its basic idea is that EEMD is employed to adaptively decompose a signal with extra white noise into a series of intrinsic mode functions with narrow-band characteristic and then Hilbert transform is applied to these IMFs. The examples have shown that the mode mixing can be decreased effectively by considering additional white noise to the signal.

Currently EEMD is utilized in the estimation of Hilbert-spectrum (Song et al., 2012) and fault diagnosis (Lei et al., 2009) and so on. The published examples have demonstrated their effectiveness. The new complete EEMD (CEEMD) presented a better spectral separation of modes (Torres et al., 2011). Also, the examples showed that CEEMD have the advantages of fewer sifting iterations and lower computational cost. Further, CEEMD is employed in seismic signal spectral decomposition and higher spectral–spatial resolution of time–frequency distribution is demonstrated (Han and van der Baan, 2012). Inspired by EMD, a new adaptive data analysis method is addressed to extract the instantaneous frequency of nonlinear and non-stationary data (Hou and Shi, 2013).

In this paper, by comparing the decomposed IMFs and corresponding instantaneous frequency based on EMD with that based on EEMD respectively, we present our new insights into the induced mode mixing problem and the improved instantaneous attribute analysis of seismic signal based on EEMD, by analyzing seismic reflection data. The rest of this paper is arranged as follows: the algorithms of EEMD and instantaneous frequency are described in Section 2. In Section 3, we respectively apply EMD and EEMD to the migration data of Marmousi2 model. The mode mixing and its influence on the estimated instantaneous frequency are studied and the advantageous EEMD based instantaneous frequency is showed. In order to further prove the effectiveness of EEMD and corresponding instantaneous frequency, a 2D field seismic data is analyzed in Section 4. Section 5 presents conclusion and discussion.

2. Instantaneous frequency based on EEMD

2.1. Ensemble empirical mode decomposition (EEMD)

As a noise-assist data analysis method, EEMD is proposed to solve the mode mixing problem (Wu and Huang, 2009), where EMD is performed on an ensemble of the signal with additional white noise rather than the original signal. Then the EMD is applied to the noisy data to obtain the IMFs. In order to make the added white noise weaken, the process described above is repeated N times and then the final IMFs are obtained by averaging all the noisy IMFs in the same level.

The main idea of EEMD is to take advantage of the statistical characteristics of white noise and add white noise into the original signal with many trials. If the added white noise level is close to the actual level and also the number of trials is sufficient, more accurate decomposition results can be obtained by EEMD. The algorithm for EEMD contains the following steps (Wu and Huang, 2009):

Step 1: For a given original signal $x(t)$ and a white noise $w_i(t)$ set to it, we constitute a new signal $y_i(t)$

$$y_i(t) = x(t) + \varepsilon w_i(t), i = 1, \cdots, N, \tag{1}$$

where i means the ith trial and N is the number of the trials. $w_i(t)$ is the added white noise with normal distribution, whose mean value is 0 and variance is 1.0. We assume that $w_i(t)$ in each trial is statistically independent, and ε is the standard deviation of white noise.

Step 2: For the ith trial, applying the EMD to the noisy signal $y_i(t)$ to obtain the IMFs noted as $c_{ij}(t), j = 1, \cdots, K$, where j is the order of IMF and K is the mode number.

Step 3: Repeating step 1 and step 2 N times.

Step 4: To weaken the added noise, the average of the decomposed IMFs with the same order is defined as the final output IMFs $c_j'(t)$

$$c_j'(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij}(t), j = 1, \cdots, K, \tag{2}$$

where the IMFs are based on EEMD and noted as E-IMFs. Then the original signal can be expressed as

$$x(t) = \sum_{j=1}^{K} c_j'(t) + r_K(t), \tag{3}$$

where $r_K(t)$ is the residue. In this paper, considering the computational efficiency and variance of white noise, we set N greater than 100 and K greater than 2. In addition, only the first and second E-IMFs are considered.

According to the procedure of EEMD and the algorithm in EMD, E-IMFs are the decomposition of the original signal. The first E-IMF $c_1'(t)$ contains the highest frequency components of signal, and the final E-IMF $c_K'(t)$ contains the lowest frequency components. Unlike Fourier transform and wavelet transform where a predetermined spectral basis is defined, EEMD and EMD depend on the characteristic of the original signal in time domain directly, which are data-adaptive. We define IMFj ($j = 1, \cdots, K$) as the intrinsic mode function $c_j(t)$ based on EMD to simplify the notation. In the same way, E - IMFj ($j = 1, \cdots, K$) is set as EEMD based intrinsic mode function $c_j'(t)$.

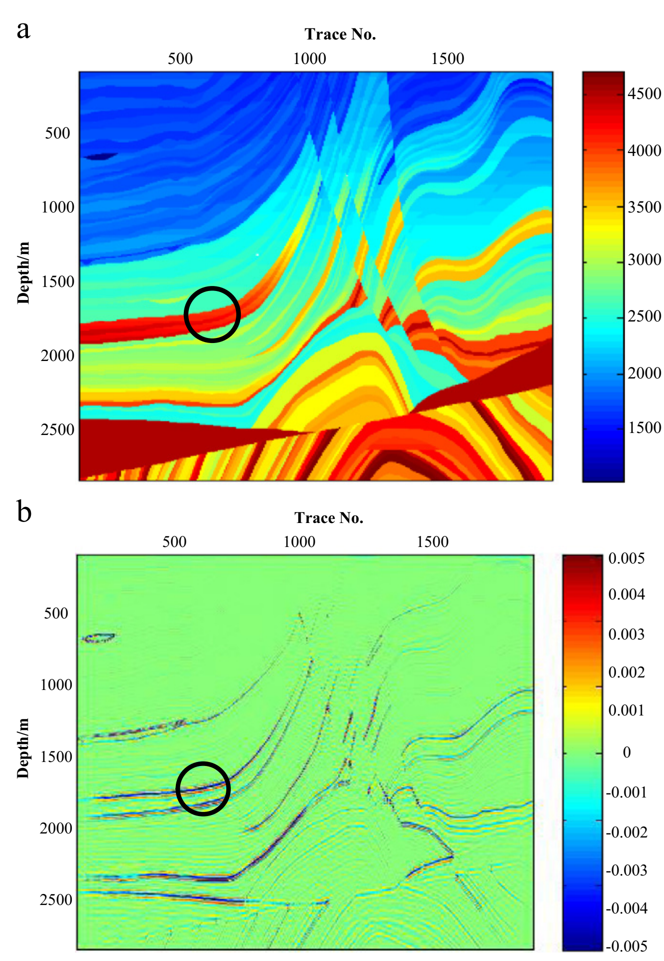

Fig. 1. Marmousi2 model: (a) the P-wave velocity; (b) wave-equation pre-stack depth-migration data.