Computers & Geosciences 88 (2016) 132–141

Contents lists available at ScienceDirect

Computers & Geosciences

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

Case study

Using an improved BEMD method to analyse the characteristic scale of aeromagnetic data in the Gejiu region of Yunnan, China

Jie Zhao*, Pengda Zhao, Yongqing Chen

China University of Geosciences (Beijing), 29 Xueyuan Road, Haidian District, Beijing 100083, China

ARTICLE INFO

Article history:
Received 12 April 2015
Received in revised form
17 December 2015
Accepted 18 December 2015
Available online 7 January 2016

Keywords:
Intrinsic mode function
Empirical mode decomposition
Characteristic scale
Metallogenic prediction
HHT

ABSTRACT

The geological and metallogenic process is a typical non-stationary multifactor and multi-scale random process. Multiple measurement data assess the performance of the integrated process, and the combined data set is usually large and complex, among other characteristics. When different metallogenic prediction targets exist, the data must be decomposed on different scales in space. The study of the scale interval in which the object features are located can eliminate useless information and retrieve useful scale data that are needed for metallogenic prediction. Thus, the model that the specific deposit presents will be rapidly and accurately identified to enhance the efficiency of the prediction and analysis models. This paper employs an improved bidimensional empirical decomposition method to decompose aeromagnetic survey data and expresses and decomposes the spatial distribution of deposits with a mixed Gaussian model. By comparing the decomposition results on various sampling data scales with the distribution function for the deposit, the characteristic scale interval that contains the measurement information that exhibits the greatest similarity to the distribution of the deposits can be identified. This method was employed to analyse a Yunnan Gejiu tin–copper polymetallic deposit using aeromagnetic sampling data to calculate suitable decomposition-scale parameters. This approach provides valuable parameters for metallogenic prediction in other areas with aeromagnetic data.

1. Introduction

Geological processes are typical, non-stationary and complex temporal and spatially variable processes (Cheng, 2003; Turcotte, 1997; Bansal and Dimri, 2005a, 2005b, 2014). A basic task of geological research is modelling this process to quantitatively and accurately describe it. Due to the extreme complexity of the entire process, reproduction of the whole geological process by establishing a single or several mathematical models is not feasible. A feasible approach is to address subproblems and subprocesses in a fractionised domain and to build a concrete model (Zhao, 1982, 2002; Zhao et al., 1994).

Geological data consists of measurement signals and a non-stationary random process that are formed by the interaction of various modulation mechanisms (Diks, 1999; Huang et al., 1996; Widrow and Stearns, 1985). Scale decomposition and scale selection of geological signals are the primary focus of this paper.

The decomposition and reconstruction of signals are classic problems. Frequency analysis tools and scale analysis tools can completely expand the structures of a signal; depending on their application, they can be employed for selecting and re-organising information to obtain a new desired signal (Cheng, 2004). This study employs the HHT as the analysis tool. The basic principle of the HHT is to decompose a signal based on the symmetry of the signal at each scale. Compositions that are decomposed from each characteristic scale are referred to as the intrinsic mode function (IMF). For each IMF, the Hilbert transform was employed and the instantaneous frequency spectrum was calculated. Then, the instantaneous spectrum of each component was combined, and information about the signal frequency structure was obtained. Therefore, the HHT is an integrated decomposition tool in the space-wavenumber domain (Kantz and Schreiber, 1997).

In recent years, there have been many applications of the HHT transform in geosciences researches (Chen and Zhao, 2011, 2012; Hou et al., 2012; Huang et al., 2010; Jian et al. 2012); however, many researchers use it as a conventional decomposition tool for sample data processing, obtaining features from various scales, and using these characteristics as parameters or input in different mathematical models. This is only a basic application of the HHT. For the former applications of the HHT for geosciences data processing is a simple signal decomposition, neither the frequency decomposition mechanism of the BEMD is discussed, nor the self-adaption of the signal analysis is made by the mechanisms, a deeper understanding of the HHT, the analysis of its mathematical

* Corresponding author.
E-mail address: dayinggezhuang@163.com (J. Zhao).

http://dx.doi.org/10.1016/j.cageo.2015.12.016
0098-3004/

properties and how to more deeply and reasonably apply the characteristics of the HHT in the geosciences are problems that remain to be studied.

In this paper, the basic principles of the HHT (Han et al., 2002; Huang, 2005, 2006) are described and its scale decomposition function is analysed. The effective scale decomposition ability of the HHT is employed to reduce a signal to an integrated multi-scale channel and identify components that are closest to the specific metallogenic mode at each scale, which is the scale interval in which the specific metallogenic mechanism serves a role. Once a scale parameter has been determined, it can be employed as a reference for metallogenic prediction or ore-forming process analyses in other locations, which is performed by directly applying the data within the decomposed characteristic scale to predict the metallogenic process using pattern recognition or feature comparison. Calculation and analysis based on decomposition data in the characteristic scale interval produces not only higher accuracy but also greater efficiency (Bedrosian, 1963; Flandrin and Gonçalves, 2004; Flandrin et al., 2004, 2005; Huang, 2001; Huang et al., 1998; Bendat, 1990).

2. HHT Analysis

The HHT method is a time-domain decomposition and frequency spectrum analysis method that was proposed at the end of the 1990s. It has the characteristics of simple calculation, strong adaptability, instantaneous spectrum structure and strong robustness. It is a new signal processing mode of decomposition and a breakthrough of various types of analysis tools based on the Fourier transform.

The HHT method employs a multi-scale analysis framework that is similar to the wavelet analysis (Schlurmann, 2002); however, it does not consider the signal frequency as the basic object of calculation. Its scale decomposition object is the symmetry of the vibration on the time domain. This change abandons the convolution calculation, which is generally adopted by the Fourier transform and wavelet analysis; it prevents the poor adaptability that is caused by the pre-setting convolution kernel and is more flexible and stable. Correspondingly, the disadvantage of this decomposition is that does not have a clear boundary in the frequency domain. For many applications, the scale analysis is more important than the frequency analysis; thus, the HHT becomes very suitable for these cases. For example, a substantial amount of geological data that corresponds to the stochastic processes are very suitable via use of the HHT. The majority of geological signals are complex, are composed of a plurality of spectrum types, are non-stationary and nonlinear (Tong, 1990; Wu et al., 2007), and are combined with many local time variation processes. Use of a highly adaptive and multiscale analysis tool, such as the HHT, which is directly based on the spatial form, to decompose signals with these characteristics is more suitable.

Numerous studies have applied HHT analysis to geoscience problems (Coughlin and Tung, 2004; Coughlin and Tung, 2005; Datig and Schlurmann, 2004; Duffy, 2004; Han et al., 2002; Huang and Attoh-Okine, 2005; Huang and Shen, 2005; Huang et al., 2001; Komm et al., 2001; Nuttall, 1966; Schlurmann, 2002; Zhang, 2006).

The HHT involves two parts: the first part is an iterative sifting process, in which an original signal is decomposed into a trend term and a plurality of the component function, which is referred to as an intrinsic mode function (IMF) (Wu and Huang, 2005). Each IMF has the characteristics of an approximate zero mean and envelope symmetry. This decomposition process is known as empirical mode decomposition (EMD). The second part uses the Hilbert transform to decompose the instantaneous frequency for each IMF to obtain instantaneous spectra of the decomposed signal (Chen et al., 2006; Huang et al., 2008). As the EMD algorithm guarantees the symmetry of each IMF signal and the zero mean characteristics, the IMF is very suitable for the Hilbert transform; some common defects of the Hilbert transform would not appear. These two parts are combined to constitute the HHT, in which the function of the first part is the scale decomposition and the role of the second part is the frequency analysis.

2.1. EMD decomposition

First, we discuss empirical mode decomposition. The decomposition rules of EMD imply some assumptions and property requirements of the HHT for signals: (1) the signal should be a concussion signal, in which minimum and maximum values can be applied to the decomposition procedure, and signals usually have multiple concussion periods, so that the analysis has practical significance; (2) the time interval between the extreme points and the amplitude of the vibration are important scale characteristics of the signal; however, the IMF enables variation in the two characteristic scales. A relatively stable characteristic scale indicates the high probability of a single vibration source; and (3) if the signal data have no extreme points but have inflection points, an extreme point can be obtained by differentiating the signal data and integrating it to obtain the decomposition results (Xu et al., 2006).

For the original signal $f(x, y)$, the specific sifting process of the EMD method is as follows: first, initialise the residual function $res(x, y)$ and the current step signal $f_0(x, y)$. Let $res(x, y) = f(x, y) = f_0(x, y)$. Second, calculate all extreme points of the current signal $f_0(x, y)$: employ a double three-spline interpolation function to calculate the upper envelope $up(x, y)$ of all local maximum points and employ this same method to obtain the lower envelope $low(x, y)$ of all local minimum points. Third, obtain the average surface $mean(x, y) = (up + low)/2$ of the two envelopes. The mean represents the development trend of the data. Fourth, the trend from the original signal. Let the remaining part be the signal of the next step, that is, $f_1(x, y) = f_0(x, y) - mean(x, y)$. Last, determine the relationship between the current step signal f_1 and the previous step signal f_0 by placing them into the stop condition. If the stop condition is not satisfied, repeat this fitting and subtracting of mean processes to obtain $f_2, f_{3,...}$ until the stop condition is satisfied. The stop criterion serves a critical role in BEMD; it determines the scale, which resembles a frequency band, for which the current pass of decomposition generates relatively stable components. Additional levels are obtained for smaller thresholds. Let the current step signal be f_n. Then, f_n is the minimum scale IMF of the first layer that is sifted, which is denoted as imf_1. Remove the decomposed intrinsic mode function imf_1 from the original signal and re-initialise the remaining part as a new residual function and a current step signal, i.e., $res(x, y) = f_0(x, y) = f(x, y) - imf_1$. Repeat this sifting process for IMF2, IMF3,…, and the final residual function $res(x, y) = f_0(x, y) = f(x, y) - imf_1$ is obtained. Their relationship is

$$f(x, y) = \sum_{i=1}^{n} imf_i(x, y) + res(x, y).$$

A flow chart of the EMD decomposition process is shown in Fig. 1.

2.2. Hilbert Transform

Consider a one-dimensional function as an example to introduce the Hilbert transform, which analyses the instantaneous frequency of the decomposed IMFs. Let the original signal be $x(t)$. The Hilbert transform is the convolution of the signal and $(\pi t)^{-1}$: