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Fast, simultaneous and robust VLF-EM data denoising and reconstruction via multivariate empirical mode decomposition

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ABSTRACT

The measurement of Very Low Frequency Electromagnetic (VLF-EM) is important in many different applications, i.e, environmental, archeological, geotechnical studies, etc. In recent years, improving and enhancing VLF-EM data containing complex numbers (bivariate) was presented by several authors in order to produce reliable models, generally using univariate empirical mode decomposition (EMD). Applying univariate EMD separately on each data is problematic. This results in a different number of misaligned Intrinsic Mode Functions (IMFs) which can complicate the selection of some IMFs for denoising process. Thus, a filtering method based on the multivariate empirical mode decomposition (MEMD) approach to decompose simultaneously bivariate data is proposed. In this paper we address two issues by employing the recently introduced noise assisted MEMD (N-A MEMD) for improving bivariate VLF-EM data. Firstly, the N-A MEMD to decompose bivariate measurement of the VLF-EM data into IMFs and a residue is defined as VLF-EM signal or unwanted noise. Secondly, the proposed method is used to enhance VLF-EM data and to reject unwanted noise. Finally, the proposed method is applied to a synthetic data with two added sinusoids. To demonstrate the robustness of the N-A MEMD method, the method was tested on added-noise synthetic data sets and the results were compared to the Ensemble EMD (EEMD) and Bivariate EMD (BEMD). The N-A MEMD gave more robust and accurate results than the EEMD and BEMD methods and the method required less CPU time to obtain the IMFs compared to EEMD. The method was also tested on several field data sets. The results indicate that the filtered VLF-EM data based on the N-A MEMD make the data easier to interpret and to be analyzed further. In addition, the 2D resistivity profile estimated from the inversion of filtered VLF-EM data results was appropriate to the geological condition.

1. Introduction

The Very-Low Frequency method is one of the electromagnetic geophysical methods that is extensively used in environmental (Al-Tarazi et al., 2008; Kaya et al., 2007; Monteiro Santos et al., 2006), archeological studies (Abbas et al., 2012), and geotechnical studies (Sharma et al., 2010), to estimate ore deposits (Bayrak and Şenel, 2012; Eze et al., 2004), to identify faults (Gürer et al., 2009), underground rivers (Bahri et al., 2008; Neumann et al., 2009; Warnana and Bahri, 2004), etc. VLF-EM data (inphase and quadrature components) is usually interpreted qualitatively (Fraser filter and Kharous and Hjelt filter) and quantitatively (inversion). The data is complex, where inphase data is the real part while quadrature data is the imaginary part, which can be called bivariate data. The processing (and inversion) results depend on the quality of the data which is usually degraded by nonlinear and non-stationary noises which cannot be rejected using linear methods.

Thus, previous researchers (Jeng et al., 2007) use the empirical mode decomposition (EMD) for non-stationary data analysis, which decomposes VLF-EM data (in-phase and quadrature) into a number of oscillatory modes, termed intrinsic mode functions (IMFs). Because decomposition results of EMD often contain mode mixing, Lin and Jeng (2010) and Jeng et al. (2012) propose ensemble EMD (EEMD) to decompose and denoise VLF-EM data. Although EEMD is able to reduce mode mixing, EEMD brings out a new problem, i.e., the residual noise is likely to remain in IMFs as a consequence of adding noise directly to the data. Thus, sometimes the decomposition process using EEMD method is not fully

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reached (Rehman et al., 2013; Torres et al., 2011). Moreover, the EMD and EEMD operate univariate signals and cannot handle multivariate data (bivariate or complex data), thus they are applied separately to the inphase and quadrature components. Because inphase and quadrature data include bivariate signals, separate analyses of both data will crucially ignore any mutual information (Mandic et al., 2008), i.e, tilt angle parameter. Analysis of multivariate data using univariate EMD may result in mode misalignment (Hu and Liang, 2011; Rehman and Mandic, 2011). This term is used to describe a condition, where, similar multivariate IMFs have different frequency modes (Rehman and Mandic, 2010a).

Several methods to analyses bivariate data have been proposed, such as complex EMD (CEMD) (Tanaka and Mandic, 2007), rotation-invariant EMD (RI-EMD) (Altaf et al., 2007), bivariate EMD (BEMD) (Rilling et al., 2007), turning tangent EMD (Fleureau et al., 2011a), and extended EMD (X-EMD) (Fleureau et al., 2011b). The problem of bivariate data decomposition using EMD approaches are mode mixing and mode misalignment (Rehman and Mandic, 2011). To reduce these problems, Rehman and Mandic (2011) proposed a different method, called noise assisted multivariate EMD (N-A MEMD), to improve IMFs at univariate and multivariate data. The N-A MEMD method uses the multivariate EMD (MEMD) algorithm (Rehman and Mandic, 2010a; Rehman et al., 2013). Even then, IMFs decomposed by N-A MEMD gave better defined subband filters as compared with EMD and EEMD (Mandic et al., 2013; Rehman and Mandic, 2011).

Thus, in this work we used the N-A MEMD approach to remove noise from VLF-EM data in order to improve and enhance VLF-EM data. To do this, we used two steps. First, we used the MEMD to bivariate VLF-EM data simultaneously to derive IMFs for each variable. Secondly, we reconstructed the VLF-EM data by computing the cumulative sums of the IMFs extracted by the MEMD. The method is tested in synthetic data and applied to VLF-EM data fields simultaneously collected in land-slide study and used to determine the location of underground rivers and phosphate deposits.

2. VLF-EM

The VLF method utilizes military radio transmitters operating in the frequency range of 15–30 kHz. A theoretical background of this method has been extensively discussed in various literatures (McNeill and Labson, 1993; Telford et al., 1990). The primary electromagnetic field of a radio transmitter (vertical electric dipole) has a vertical electric field component (EP_z) and a horizontal magnetic field component (HP_y) which propagates perpendicularly to the direction of x (Fig. 1). At a distance greater than several free wavelengths from the transmitter, the primary EM field components can be assumed as horizontally traveling waves. HP_y penetrates into the ground and induces a secondary horizontal electric component (ES_x) in buried conductive structures with an associated magnetic field (HS). The secondary magnetic field acquires horizontal and vertical components. This secondary EM field has parts oscillating in-phase and quadrature with the primary field. The intensity of the secondary EM field depends on the conductivity of the ground.

The VLF-EM method measures the resultant local horizontal and vertical magnetic field components with two orthogonal induction coils. The local resultant magnetic field HR is the superposition of the primary field HP and secondary field HS, where HP$\gg$HS. In the presence of an underground conductor, the total VLF field is elliptically polarized. Furthermore, results of the VLF-EM are the inphase (real) and quadrature (imaginary) parts of the ratio (HR_z/HR_y). The real and imaginary components are expressed as a percentage of the total VLF transmitter's primary field. The real part of the tipper is sensitive to low resistivity bodies while the quadrature part of the tipper is

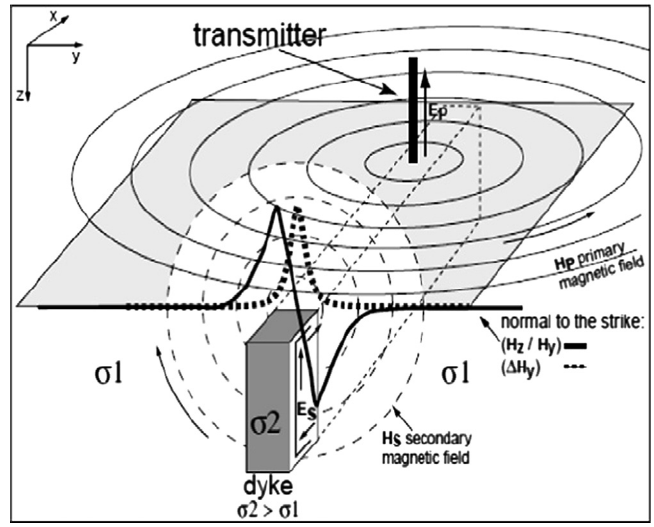

Fig. 1. EM field distribution for the VLF method in polarization with theoretical signals over a vertical conductive dike (Bosch and Müller, 2001).

sensitive to variations of the earth electrical properties (Monteiro Santos et al., 2006).

Generally, interpretation of VLF-EM can be done through qualitative and quantitative approaches. Qualitative interpretation commonly used Fraser filter (Fraser, 1969) or K–Hjelt filter (Karous and Hjelt, 1983) to identify the location (lateral) of the resistive and conductive zones while quantitative interpretation used inversion method to derive 2D subsurface resistivity. Monteiro Santos et al. (2006) developed a software (Inv2DVLF) for quantitative interpretation of single-frequency VLF-EM data inverting the tipper data with a 2D regularized inversion approach (Sasaki, 2001). The code was developed based on a forward solution using the finite element method (FEM).

3. Univariate emprical mode decomposition (EMD)

EMD is a fully adaptive method for multiscale analysis of non-linear and non-stationary real signals (Huang et al., 1998). The first objective of this algorithm is to decompose univariate signals. EMD decomposes the data into a finite number of simple orthogonal oscillatory modes called intrinsic mode functions (IMFs) which fulfill two conditions: (1) the number of extrema and the number of zero crossings must be equal or differ at most by one and (2) the mean value of the local maxima (upper envelopes) and local minima (lower envelope) is zero in everywhere.

The EMD algorithm decomposes the original signal into IMFs and a residue. For real signals $x(t)$, the standard EMD estimates a set of N IMFs $\{c_i(t)\}_{i=1}^{N}$ and a monotonic residue signal $r(t)$, so that

$$x(t) = \sum_{i=1}^{N} c_i(t) + r(t) \quad (1)$$

The EMD is highly adaptive and consequently can satisfactorily descript the time-frequency characteristics of a signal. EMD algorithm uses an iteration process to derive the IMFs. An iteration process called sifting process is employed. For example, a sifting process for obtaining the first IMF from signal $x'(t)$ includes the following steps (Huang et al., 1998):

(1) Estimating all local minima and local maxima of $x'(t)$.
(2) Interpolating all the local minima to obtain the lower signal envelope and then interpolating all the local maxima to estimate the upper signal envelope.