The Empirical Mode Decomposition (EMD), a new tool for Potential Field Separation

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Abstract: In this paper we are proposing the use of the Empirical Mode decomposition method as a tool for potential field data separation. The empirical mode decomposition (EMD) is a new data analysis method suitable to process non-stationary and nonlinear data. Its power to filter and decompose data has earned it a high reputation in signal processing. Its decomposition results in what is called "Residual", which is similar to the regional anomaly of a potential field data. This residual does not require any preset parameters unlike contemporary field separation methods. The method is applied to a magnetic data from the Jianshandian mine in Hubei, China enabling us to construct a 2.5D inverse model inferring the existence of deep ore deposits. The method is effective at separating both local and regional data from magnetic data. [Journal of American Science 2010;6(7):183-187]. (ISSN: 1545-1003).

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1.0 Introduction

Geophysical potential field separation is a process in which the regional and the local anomalies are separated. Generally, regional anomaly is associated with a larger amplitude and scope but smaller horizontal gradient caused by the widely distributed mid-deep sources; while the local anomaly is vice versa. There are several field separation methods in use today based on Fourier or wavelet transforms. The Fourier transform (FFT) is designed to work with linear and stationary signals. The wavelet transform, on the other hand, is well-suited to handle non-stationary data, but it is poor at processing nonlinear data (Hassan and Pierce, 2008). Prominent among these methods are Polynomial fitting, moving average, upward and downward continuation and wavelength filtering. The regional anomalies obtain via these methods depend largely on preset parameters. Moreover, geophysical data are nonlinear and non stationary.

The combination of the well-known Hilbert spectral analysis (HAS) and the recently developed empirical mode decomposition (EMD) [Huang *et al.*, 1996, 1998, 1999], designated as the Hilbert-Huang transform (HHT) by NASA, indeed, represents a paradigm shift of data analysis methodology. The key part of HHT is EMD with which any complicated data set can be decomposed into a finite and often small number of intrinsic mode functions (IMFs). This decomposition method is adaptive and therefore highly efficient. As the decomposition is based on the local characteristics of the data, it is applicable to nonlinear and nonstationary processes. Contrary to almost all the previous decomposition methods, EMD is empirical, intuitive, direct, and adaptive, without pre-determined basis functions (Huang & Wu., 2008). It has been applied in severals fields such as meteorology (Iyengar and. Kanth,2005), signal processing (Linderhed, .2004),and geosciences (Hassan and Pierce, 2008) The decomposition is designed to seek the different simple intrinsic modes of oscillations in any data based on local time scales. A simple oscillatory mode is called intrinsic mode function (IMF) which satisfies: (a) in the whole data set, the number of extrema and the number of zero-crossings must either equal or differ at most by one; and (b) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The residual value obtained by removal of a series of IMFs is the trend component that represents the average trend, which is similar to the geophysical regional anomaly. In light of the power of the EMD as a decomposer, we are proposing its use as a potential field separator.

2.0 Material and methods

2.1 Study Area

Our area of study is Jinshandian ore mine in located in Hubei, China and characterized as a typical contact metasomatic deposit bed. It is distributed in or around the contact zone of the monzonite granite and Triassic sandstone and shale (fold in the carbonate rocks), with a north-west (NW) strike direction and a length of 3km approximately (Fu *et al*, 2008) It contains several cluster of deposits. It is an open mine and extraction of mineral has been ongoing reaching a depth of 400m. Based on the geological background, ore geology, gravity and magnetic abnormities and coupled with a large scale residual gravity and magnetic anomaly, it is predicted that concealed ore bodies could be at greater depth than those already known. Profile AA' is taken in the southern portion away from the main ore body to deduce the presence of magnetite at this part (fig.1).

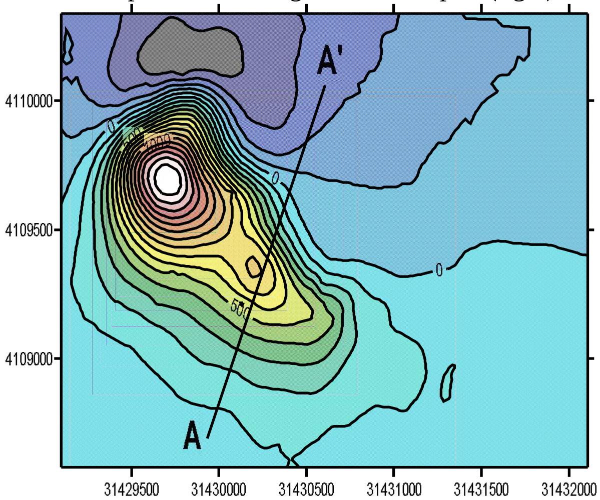


Figure 1: Aeromagnetic map of Jianshandian showing profile AA'

2.2 Principle of the EMD

The EMD is an adaptive decomposition technique with which any complicated signal can be decomposed into a definite number of high-frequency and low frequency components by means of a process called "sifting". The sifting process decomposes the original signal, $S(x)$, into a number of intrinsic mode functions (IMFs) according to the following formula:

$$S(x) = \sum_{i=1}^{n} c_i(x) + r_n(x) \qquad (1)$$

Where $r_n(x)$ is the residual after n IMFs and $c_i(x)$ the IMFs.

These IMFs have well-behaved Hilbert transforms and are defined as functions that:

(a) have the same number of zero- crossings and extrema, and

(b) the mean value of the upper and the lower envelopes is equal to zero.

A sifting process extracts IMFs from the signal iteratively sequentially to obtain a component that satisfies conditions mentioned above. The sifting process separates the IMFs with decreasing order of frequency, i.e., it separates high frequency component first and the low frequency component at the end. The IMFs obtained by sifting processes constitute an adaptive basis. This basis usually satisfies empirically all the major mathematical requirements for a time series decomposition method, including convergence, completeness, orthogonality, and uniqueness, as discussed by Huang et al. [1998]. The EMD technique (Huang et al., 1998) is illustrated in Figure 2 for a simple signal consisting of chirp. The technique happens to naturally cope with superimposed smooth trends (Flandrin, P., Rilling, G., and Gonçalvés, P., 2004). The decomposition of the signal into IMFs is performed as follows:

1. Identify the positive peaks (maxima) and negative peaks (minima) of the original signal.
2. Construct the lower and the upper envelopes of the signal by the cubic spline method. *(U(t), L(t))*
3. Calculate the mean values by averaging the upper envelope and the lower envelope. $m(t)= (U(t) + L(t))/2$
4. Subtract the mean from the original signal to produce the first intrinsic mode function *IMF1* component. $S(t) - m(t) = h(t)$ *note* $h(t) = IMF1$
5. Calculate the first residual component by subtracting *IMF1* from the original signal. This *IMF1* component is treated as a new data and subjected to the same process described above to calculate the next IMF. $S(t) - h(t) = r(t)$
6. Repeat the steps above until the final residual component becomes a monotonic function and no more IMFs can be extracted.

The sifting process produces a set of *IMF*s that represent the original data vector broken down into frequency components from highest to lowest frequency. This process is subject to a symmetry condition called the stoppage (of sifting criteria) which is a normalized squared difference between two successive sifting operations. In this paper we use the one by Huang *et al* (1998) giving as:

$$SD_k = \frac{\sum_{t=0}^{T} \left[h_{k-1}(t) - h_k(t) \right]^2}{\sum_{t=0}^{T} h_{k-1}^2(t)} \qquad (2)$$

A value of 0.2 ~ 0.3 for SD is considered acceptable for a calculated IMF, that is *h(t)*. If all of the IMFs for a given signal are added together, the resulting "summation" signal is a near perfect match for the original signal (i.e., with little or no leftover), yielding a high level of confidence in the EMD results.

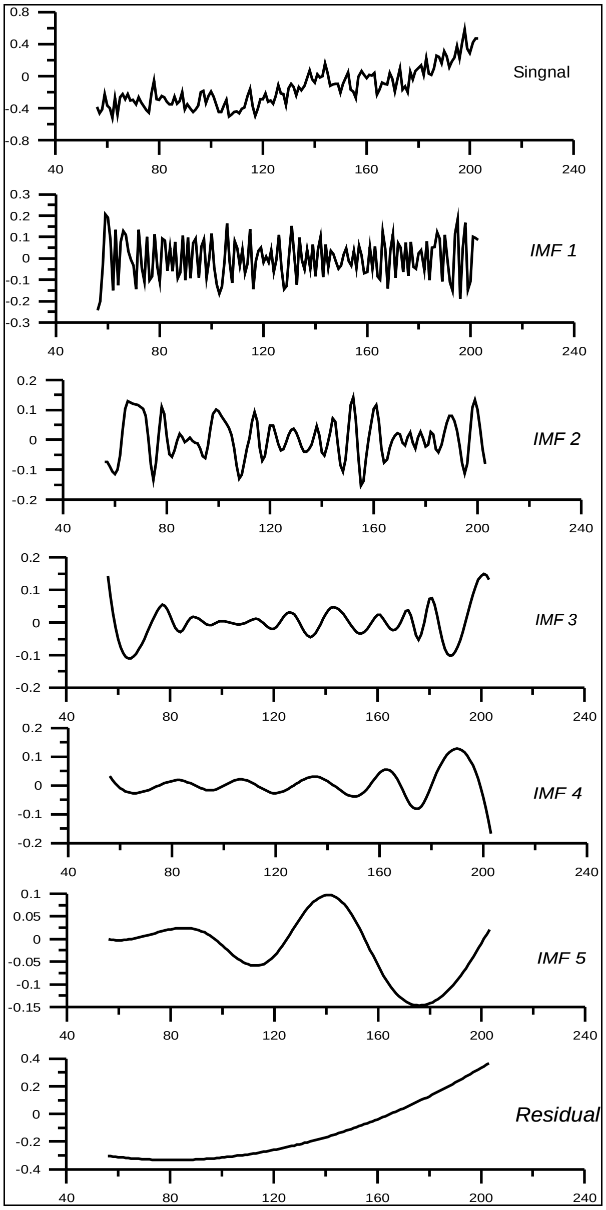


Figure 2: An empirical mode decomposition (EMD) of a signal producing five IMFs and a residual. The first curve is the plot of a chirp

3.0 Result and Discussion

To separate the regional and the local anomalies from the superinposed total magnetic anomaly profile , we use the Empirical Mode Decoposition resulting into seven IMFs and a residual(fig. 3), which is equivallent to the regional anomaly when applying conventional mehtods. The same profile was seperated using trend analysis and the result showed that the lacal and the original anomalies are almost the same signifiyingthat the complexity of the anomaly was due largely to shalow sources.

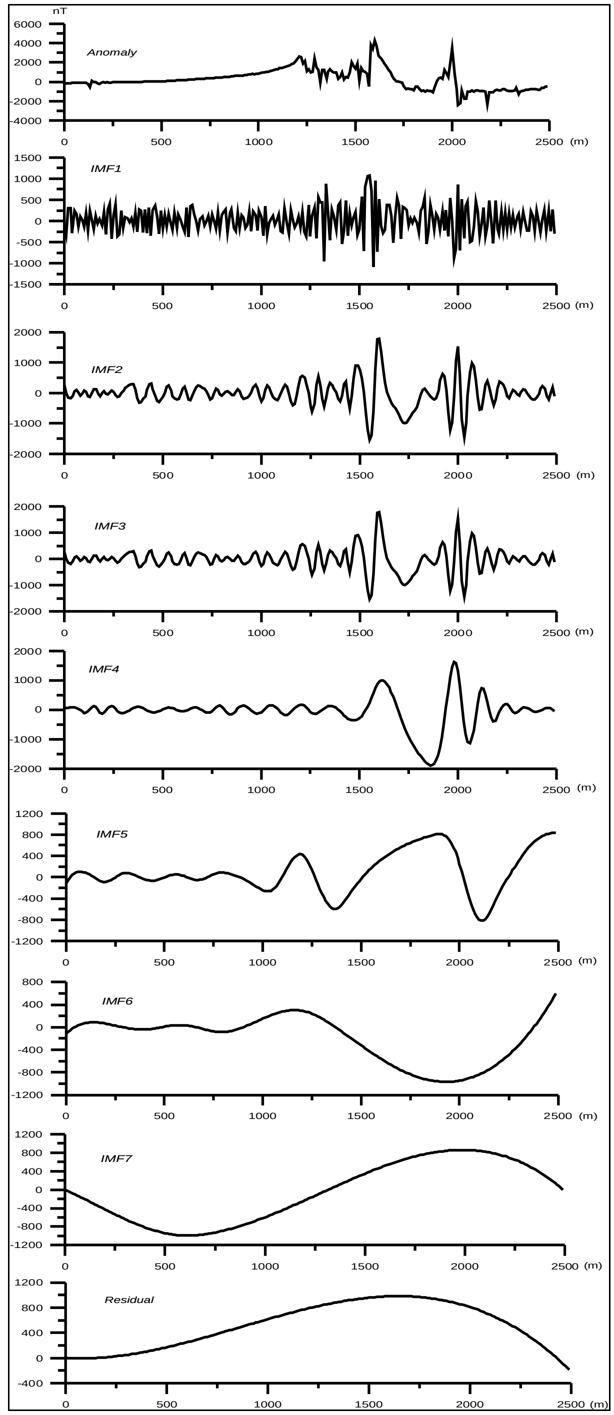
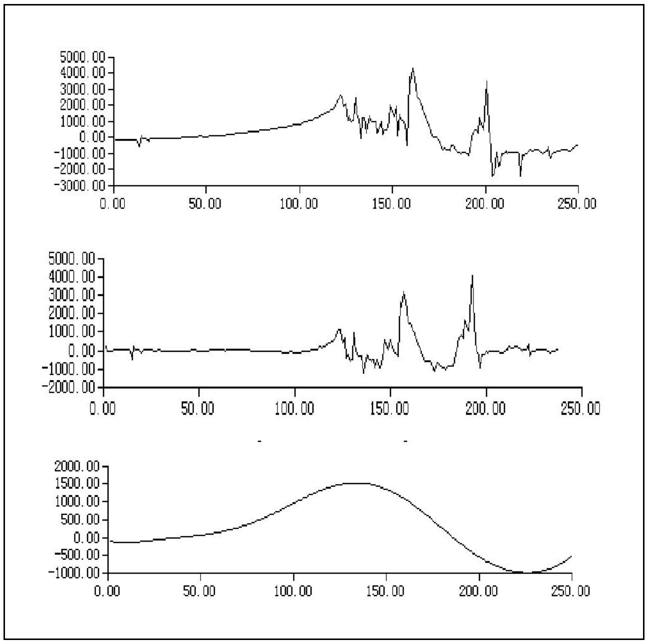


Figure 3: An Empirical mode decomposition of



profile AA’ showing seven IMfs and a residual. The topmost graph is the anomaly of the magnetic profile.

Figure 4: A trend analysis field seperation of profile AA’. The top is the total anomaly, the middle is the local anomaly and the bottom is the reginal anomaly.

The anomaly(fig.4) produced as a result of profile AA’ clearly shows serious suprficial interferences and the presence of shallow bodies thus resulting to an abnormal complex form. Fitting such curves to the theoritical values and infering deep sources can sometimes be difficult. However, from magnetic survey and the drilled core, blastopsammite, hornfels, skarn (with thin magnetite) as well as some other rocks, such as diorite, diorite porphyrite and diabase are known to be interbeded in the sandstone at the south edge of this area. They possess some degree of magnetism, which is the main factor of influence.

Magnetic parameters were based on the above analysis and in consideration of the drill core results in constructing the 2.5D forward and inverse models (fig. 5 & 6). Since the local anomaly is similar to the total anomaly, this indicates that the local anomaly mainly reflects the anomaly of the rocks and deposits at shallow depth. From 2.5D inverse model based on the EMD residual, which is similar to the regional anomaly obtained via trend analysis, we deduce that there may be 2 unknown iron deposits at greater depths. The deposits colored red and yellow have different magnetizations. The one marked yellow was partially penetrated during drilling and found to be iron III. We believe that a thick section of magnetite lie beneath this low grade. ore below the level of -400m (Fig.6), which is in conformity with assumptions based on potential field data analysis in the area (Fu Qunhe,Li Langtian, Kuang Qingguo, Zhao Zhixiang 2008).

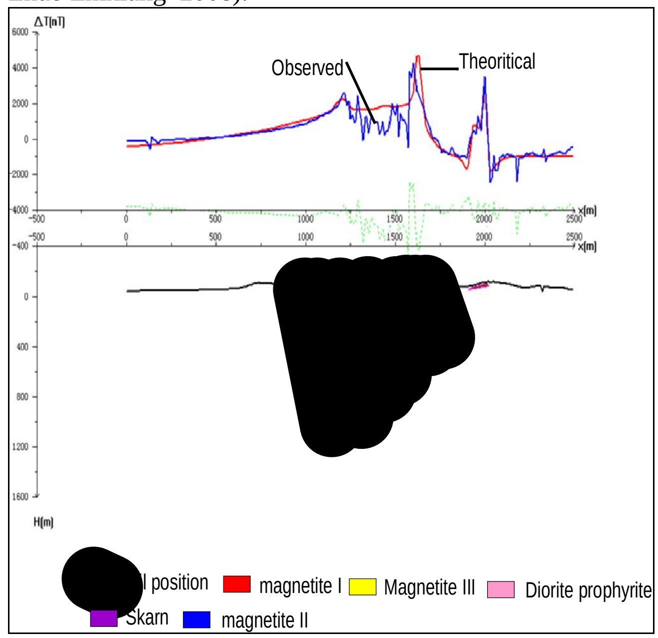


Figure 5: 2.5D forward model of the profile AA’. The black lines indicate drill positions

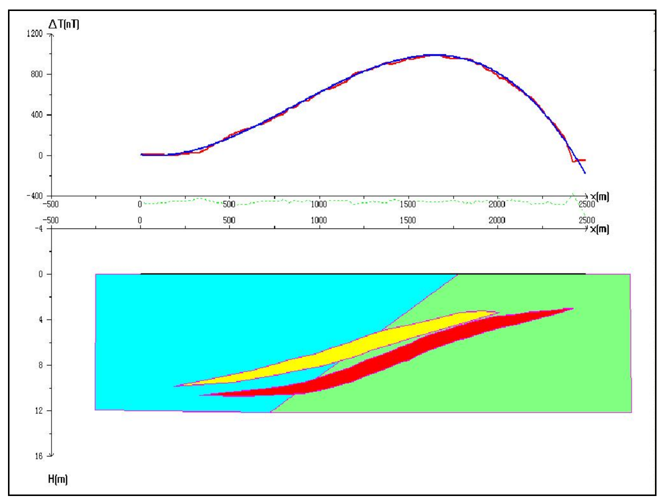


Figure 6: 2.5d inverse model based on the the residual of the EMD

4.0 Conclusion

In this paper, the EMD is proposed and applied in the separation of geophysical potential field superimposed anomalies caused by several anomalous sources. The EMD is a new and powerful technique use to analyze nonlinear and non-stationary signals such as potential field data. It decomposes the signal to a summation of zero-mean AM-FM components, called Intrinsic Mode Functions (IMF). These IMFs show the main components of the analyzed signal The EMD was applied to a magnetic data from Jianshandian iron deposit in Hubei, China and found to be effective at separating the local and regional from magnetic data and the result was compared to that of trend analysis and found to be similar. The separation was carried out without any pre-set parameters as done in traditional separation methods. A 2.5D inverse model was realized from the residual of the EMD resulting into an inference of ore bodies at greater depth below 400m.

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