Remove the HFM noise by using Wavelet Neural Network

Xin Wu¹²³, Guoqiang Xue¹²³, Zhou Zhou¹²³ and Zhao Yang¹²³

¹ Institute of Electronics, Chinese Academy of Sciences, Beijing, China
² Key laboratory of mineral resources, Institute of Geology and Geophysics, Chinese Academy of Sciences, Beijing, China
³ Chinese Academy of Sciences University, Beijing, China

Abstract. During the HTEM signal processing we found that some kind of short-term noise till remained after the conventional denoising procedure. It is called high frequency motion-induced noise according to the research on its induced mechanism and time-frequency features. In this paper, we propose an approach to suppress the high frequency motion-induced noise based on wavelet neural network. The method uses high frequency motion-induced noise as a sample and then trains the wavelet neural network by it. After processing the field data, it is considered that the method proposed in this paper can effectively suppress the high frequency motion noise and the processing results build a good data foundation for subsequent processing.

1. Introduction
Since helicopter-borne transient electromagnetic system and HTEM appeared, it is widely applied into mineral prospecting, ground water and salinity studies, bathymetry of shallow seas and coastal regions and geological hazards [1-3]. In HTEM measurement, the motion noise is one of the main noises, which is generated by the changes of the magnetic flux in the coil due to the movement of observation coil in the geomagnetic field [4]. It is necessary to remove this kind of Motion-induced Noise to improve the interpretation resolution.

High frequency motion (HFM) noise has a huge impact on the data, and the data affected by HFM noise cannot be used any more. In this paper, we will firstly study the characters of HTEM noise using field measurement data and analyze difficulties met when processing HFM noises by conventional denoising procedure. Then we propose an approach to eliminate the high frequency motion-induced noise based on wavelet neural network. We use a synthetic example to describe the above method in detail and apply it to the measured data processing. After the data processing, we find that the field data can satisfy the application requirement in the HFM noise processing of HTEM.

2. Algorithm
2.1. Traditional low frequency motion noise removal method
For conventional motion noise, since it is mainly related to the filing speed of flying platform and the inhomogeneity of the geomagnetic field, the frequency range is generally lower than that of transient electromagnetic response under the condition of stable flying and good weather, which would be called low frequency motion noise in the later passage. Therefore, the processing of low frequency motion noise can actually be regarded as high-pass filtering.
2.2. Definition of High frequency motion-induced noise

Using the first half cycle of the second cycle after the traditional noise processing in Figure 1, we carry out the spectrum analysis and compare it with the spectrum of the second half cycle of the fourth cycle without the above high-frequency vibration. The result is shown in Figure 2. From Figure 2, we find that the high frequency vibration contained in the data of the first half of the second cycle appears mainly in the range of 0.1 to 5 kHz, and the peak appears around 500 Hz.

2.3. Method of removing HFM noise

The analysis of the characteristics of HFM noise shows that as the HFM noise overlaps with the useful signal in the frequency range, the traditional motion noise removal algorithm cannot effectively remove HFM noise. Thus it is difficult to separate them on the spectrum. Taking the EMD method as an example, the main IMF component decomposed by it still contains the useful signal and HFM noise at the same time like the original signal. We cannot suppress noise by processing the specific IMF component. An approach based on wavelet neural network is proposed to overcome the difficulties of the traditional methods in processing HFM noise.
Based on the physical fact that there are differences in time between the useful signal and the HFM noise, the basic process to realize the HFM noise suppression using the WNN method can be summarized as: 1) using data which only contains HFM noise to train WNN. This equals to establishing HFM model; 2) using the model to predict the HFM noise contained in the data including useful signal; 3) deduct the HFM noise from the observed data to suppress the HFM noise (Figure 3).

The key issues to implement the process above is the second step. Its basic steps are as follows.

**Design WNN structure:** determine the number of elements contained in each layer of WNN according to the characteristics of the signals.

**Initialize the network:** randomly initialize the scaling factor $a_k$, the translation factor $b_k$, the input and output connection weights of the wavelet functions involved in calculation and set the learning rate.

**Predict output:** calculate the input value of each node of hidden layer

$$h_j = \frac{\sum_{i=1}^{m} w_{ij} x_i - b_j}{a_j}$$

(1)

where $w_{ij}$ represents the weight of input connection. Then plug the input value of each node of hidden layer into the parent wavelet basis function $\Psi$ and calculate the output value of hidden layer:

$$H_j = \Psi(h_j)$$

(2)

Last calculate the output value using the weight of output connection $\lambda_{jk}$:

$$Y_k = \sum_{j=1}^{l} \lambda_{jk} H_j$$

(3)

**Correct the weight:** calculate network prediction deviation:

$$err = \sum_{k=1}^{m} Y_k^p - Y_k$$

(4)

where $Y_k^p$ represents the desired output value. Correct the scaling factor, the translation factor and the weight of neural network connection of wavelet function according to $err$:

$$\phi^{(i+1)} = \phi^{(i)} + \Delta \phi^{(i+1)}$$

(5)

In which $\phi^{(i)}$ represents the $i$th iteration value, $\Delta \phi^{(i+1)}$ represents corrections.

$$\Delta \phi^{(i+1)} = - \eta \frac{\partial err}{\partial \phi^{(i)}}$$

(6)

where $\eta$ represents the learning rate factor. Note that when different learning rates are used in the input and output process, calculating the updating weight value of the output connection requires using the learning rate factor of the output process itself.
2.4. Field data example
We test our method on the data acquired from a copper polymetallic deposit in North of China. The result is shown in Figure 4. From the results, we find that after our data processing, the HFM noise is well suppressed. Our method can build a good data foundation for subsequent processing.

![Figure 4](image-url)

**Figure 4.** Comparison between the result of removing noise and neighboring period data

3. Conclusions
During testing of HFM, we found that there was high frequency motion (HFM) noise in the measured data because of the short-term airflow and the change of flight conditions. We propose a new method to suppress the HFM noise based on wavelet neural network. The method uses HFM noise in dominance to train the WNN. After the field data processing, we are confirmed that the method proposed in this paper can effectively suppress the HFM noise and the processing results can build a good data foundation for subsequent processing.

References
[1] Sørensen K I and Auken E 2003 New developments in high resolution airborne TEM instrumentation ASEG 16th Geophysical Conference and Exhibition, Adelaide
[2] Witherly K, Irvine R and Morrison E B 2004 The Geotech VTEM Time Domain Helicopter EM System SEG Int’l Exposition and 74th Annual Meeting, Denver.
[3] Vrbancich J 2007 Bathymetry and sediment depth investigation in Broken Bay using a prototype AEM time domain system (SeaTEM) ASEG 2007, Perth
[4] Macnae J C, Lamontagne Y and West G F 1984 Noise processing techniques for time-domain EM systems Geophysics 49(7) 934-948