

Research on the Noise Suppression of The TEM Signal by Neural Network

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Abstract: The Groud-source Airborne Time-domain Electromagnetic(GATEM) system is susceptible to interference during flight, including motion noise (caused by factors such as wind direction, cable vibrations, and sensor attitude), power frequency noise, and atmospheric noise. To obtain field data, and enhance the precision of abnormal target identification, it is necessary to suppress noise to the field data. In this paper, a neural network approach is employed to reconstruct the GATEM signals. This includes the establishment of a sample sets, parallel numerical simulation method of GATEM responses based on the OpenMP, deployment and execution of parallel computing programs on cloud computing platforms, and neural networks implementation for noise suppression in noisy GATEM signals. When the signal-to-noise ratio is above 30dB, the error between the denoised signal and the original signal is very small, with an average relative error not exceeding 1%. This method can effectively improve the accuracy of interpretation and imaging of GATEM signals, opening up new research directions in noise suppression for electromagnetic signals.

1. Introduction

The GATEM system possesses advantages such as high efficiency and deep exploration depth, making it suitable for rapid geological surveying in special conditions, such as mountainous areas and coastal zones. Time-domain electromagnetic signals are susceptible to interference from motion noise, power frequency noise, and atmospheric noise. The interference is particularly severe for late signals, and the effective extraction of late signals directly affects the interpretative accuracy of deep exploration.

Scholars have conducted extensive work in recent years to address the noise suppression issue in time-domain electromagnetic signals. Qiu et al. (2006) applied wavelet transform to remove noise from time-domain electromagnetic data and analyzed the denoising results under different threshold conditions. The heuristic threshold was found to be more suitable for noise reduction in time-domain electromagnetic data. Bouchedda et al. (2010) used wavelet transform to restore the effective electromagnetic signal, eliminating the atmospheric noise from the data. Liu Xiangping et al. (2011) employed an improved independent component analysis method to remove power frequency interference from transient electromagnetic data, achieving good results. Reninger (2011) applied singular value decomposition to suppress atmospheric noise in airborne electromagnetic data. Chen Bin et al. (2014) effectively removed natural and human noise in time-domain airborne electromagnetic data by component analysis and applied it in the field data. Xu Ting et al. (2014) used a data-driven empirical mode decomposition algorithm to suppress wideband noise in transient electromagnetic decay curves without waveform distortion. Hou Sian et al. (2017) implemented random noise suppression and signal reconstruction in multi-channel seismic data by the K-SVD method. Liu Yiru et al. (2018) employed a Gaussian process regression algorithm to remove atmospheric and random noise from airborne transient electromagnetic data, although

the late signals were relatively less satisfactory. Liu Fei et al. (2019) changed the mechanical vibration frequency from the TEM signal by combining parallel cable technology and air-core coil sensor, thus achieving an efficient separation of mechanical vibration frequency and TEM signal frequency.

This study focuses on the issues that exists in the noise suppression field. The main research contents consist of three aspects: the shared-memory parallel numerical simulation of the Groud-source airborne time-domain electromagnetic responses by OpenMP, the deployment and execution of OpenMP parallel computing programs on public cloud, and finally, the reconstruction of the GATEM signals by neural network methods.

2. Methodology

2.1. The GATEM Numerical Simulation for Layered Model

The expression for the frequency-domain magnetic field response in the z direction for a grounded long wire source is as follows:

$$H_z = \frac{I}{4\pi} \int_{-L}^L \frac{y}{R} \int_0^{\infty} (1+r_{TE}) e^{\lambda z} \lambda J_1(\lambda R) d\lambda dx' \quad (1)$$

where L is the half-length of the grounded wire, I is the transmitting current, x is the x -coordinate of the observation point, y is the y -coordinate of the observation point, z is the z -coordinate of the observation point, $R = \left[(x-x')^2 + y^2 \right]^{1/2}$,

λ and x' are variable of integration, and J_1 represents the Bessel function. The reflection coefficient for a uniform half-space model is denoted as $r_{TE} = \frac{\lambda - \sqrt{\lambda^2 + i\omega\mu_0\sigma}}{\lambda + \sqrt{\lambda^2 + i\omega\mu_0\sigma}}$,

$i^2 = -1$, ω is the angular frequency, σ is the electrical conductivity, and μ_0 is the magnetic permeability of the vacuum. By integrating equation (1) and then performing a time-frequency transformation, you can obtain the time-domain electromagnetic response V_z .

2.2. OpenMP

The OpenMP is a multi-threading design approach that is based on the shared memory and leverages multi-core processors for parallel computing. It is suitable for a single computer and provides API specifications that support programming in C, C++, and Fortran, which makes it being suitable for parallel program design on multiprocessor computers. In the case of calculating the electromagnetic response for a single measurement point based on the layered model, the computation time typically ranges from 2 to 4 seconds. When there are many measurement points, performing these calculations sequentially would require an astonishing amount of time. Therefore, this paper employs parallel computing to get the electromagnetic response. Prior to parallel computing, it is necessary to configure OpenMP in Dev-C++, then the program's for loops can be parallelized.

2.3. Cloud Computing Platform

Parallel computing is an effective method to overcome the drawbacks of slow sequential computing and improve computational efficiency. Cloud computing, as an emerging parallel computing approach in recent years, is based on a network computing model, providing users with access to computational resources, storage, and applications. The parallel acceleration method based on a cloud computing platform for the GATEM responses includes the following steps:

1. In this paper, a cloud computing platform is established by installing Hadoop on six computational sub-nodes.
2. The GATEM response based on the layered model is employed in C++ programme.
3. Variables such as electrical conductivity and layer thickness are created as text files and uploaded to the Hadoop distributed file system.
4. Parallel electromagnetic response based on OpenMP are carried out on individual computing node.
5. The computation results are then uploaded back to the main computing node.

2.4. Neural Networks

Neural networks have gained widespread application in various fields in recent years, and achieved notable successes. When applying neural network methods to noise suppression in the GATEM data, it is crucial to find the most suitable number of layers and neurons per layer for the specific problem at hand. Additionally, considerations must be given to issues like parameter initialization and modifying the learning rate. Proper parameter initialization can lead to faster convergence of training loss while avoiding getting stuck in local minima. During the initial stages of training, a relatively large learning rate is often set to enhance efficiency. In the later stages of training, the learning rate is typically reduced in some manner to further decrease training loss.

In this paper, a sample sets for the GATEM responses are constructed by OpenMP and a cloud computing platform. Random noise based on different signal-to-noise ratios is

added to the samples. A suitable neural network model is built and trained by the training dataset. The training results are then used to predict the electrical conductivity of the test sets. Subsequently, the predicted electrical conductivity obtained from the training dataset is used for reconstruction to improve the effectiveness of noise suppression in the data.

3. Results

3.1. OpenMP Test Results

We use the OpenMP to reconstruct the program, primarily by parallelizing the for loops. Taking a three-layer model as an example, with the electrical conductivity 0.005S/m of the first layer, the second layer 0.033S/m, and the third layer 0.002S/m, and the thickness 390 m of the first layer, and the thickness 550m of the second layer. The length of the long grounded electric source is 2000 m, the transmitter current $I = 40$ A, the receiver coil equivalent area $S = 2160$ m², and the receiver location coordinates $x = 45$ m, $y = 45$ m, $z = 30$ m. The serial and parallel execution results are shown in Figure 1, where the solid line represents the serial execution result, and the dashed line represents the parallel execution result. From Figure 1, it can be observed that the curves completely overlap, demonstrating that parallelizing the program by OpenMP does not affect computational accuracy. OpenMP provides different scheduling options, including static scheduling, dynamic scheduling, and heuristic scheduling. These different scheduling options can lead to variations in program execution times.

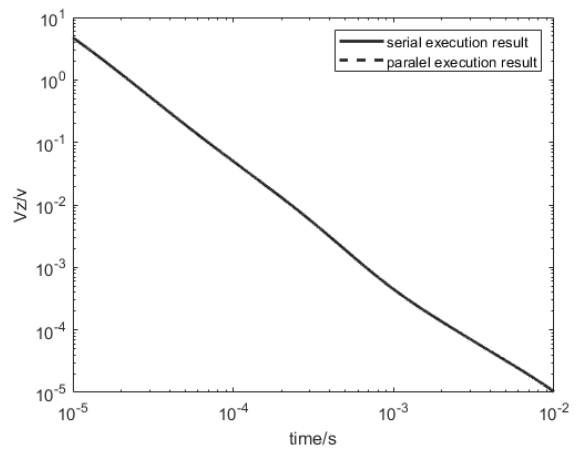


Figure 1. The GATEM responses for serial and parallel execution results

The GATEM responses were generated on an Intel(R) Core(TM) i9-10900K CPU@3.70GHz and 128GB RAM. For the three-layer model, the serial computation time is 8.6 seconds. When using static scheduling, the program's computation time is reduced to 2.16 seconds, resulting in a speedup of 3.98. With dynamic scheduling, the program's computation time is further reduced to 2.01 seconds, achieving a speedup of 4.28. When using heuristic scheduling, the program's computation time is minimized to 1.85 seconds, with a speedup of 4.64. It can be observed that the heuristic scheduling leads to the most significant improvement in efficiency, as shown in Table 1.

Table 1. Comparison of Different Scheduling Methods

	Computation Time (s)	Speedup
Serial Program	8.6	-
Static Scheduling	2.16	3.98
Dynamic Scheduling	2.01	4.28
Heuristic Scheduling	1.85	4.64

3.2. OpenMP + Cloud Computing Test Results

To compare the computational efficiency of the OpenMP + cloud computing method, this paper takes the uniform half-space model as an example and calculates the GATEM responses for 10 sets to 290 sets, with intervals of 20. The electrical conductivity varies uniformly from 0.001 S/m to 1 S/m. The specific calculation steps are as described in Section 1.3. The speedup for varying numbers of computational models is shown in Figure 2. From the Figure 2, it can be observed that as the number of computational models increases, the speedup also increases, but the rate of increase gradually slows down. When the number of models is up to 290, the speedup can reach 11.37.

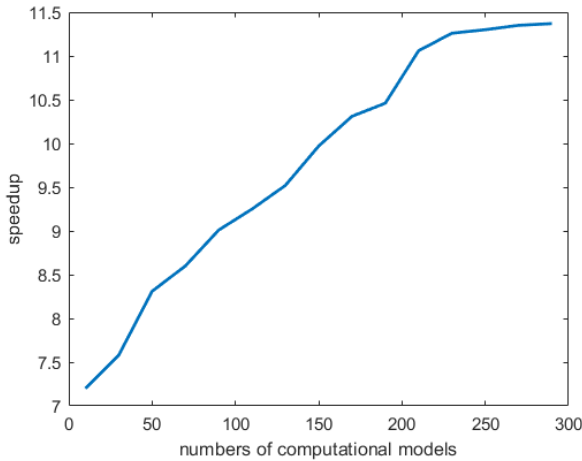


Figure 2. Speedup for varying numbers of computational models

3.3. Denoising Results for the Neural Network

To create a sample library for the time-domain electromagnetic responses of a long wire source, different sets of electrical conductivity-depth properties are first defined. Since the first layer in the actual geological structure is typically soil or sandstone with lower electrical conductivity, the range of electrical conductivity values for the first layer is chosen to be from 0.01 S/m to 0.1 S/m, while the second and third layer's electrical conductivity ranges from 0.1 S/m to 1 S/m. In a three-layer model, the total number of samples is the product of the number of possible values for each layer's electrical conductivity. To control the number of samples, it's necessary to adjust the step size appropriately. Thus, the step size for the first layer is set at 0.003 S/m, while the second and third layers have a step size of 0.02 S/m. This results in a total of 65,596 samples. The depths of the first and second layers are both 80 meters, while the third layer's depth is considered infinite. Next, Gaussian white noise is added to the calculated samples to achieve signal-to-noise ratios of 20dB, 30dB, 40dB, 50dB, and 70dB. During training, 60,000

random samples are selected to form the training dataset, while the remaining 5,596 samples constitute the testing dataset. Before training with a neural network, data preprocessing is performed, typically normalizing the data to the [0,1] or [-1,1] range. In this particular problem, since both electromotive force and electrical conductivity are positive values, normalizing them to the [0,1] range is more appropriate.

In general, the representational capacity of a neural network increases with the number of layers and neurons. However, adding more layers and neurons can lead to a significant increase in training costs and a higher risk of overfitting. Therefore, in this paper, a two-layer neural network is used, with each layer containing 128 neurons. During the training process, a variable learning rate approach is employed, starting with an initial learning rate of 0.01. When the training loss does not show significant improvement for 10 steps, the learning rate is multiplied by 0.01. The activation function for the hidden layer neurons is the Rectified Linear Unit (ReLU). After making predictions on the test dataset samples, the electrical conductivity is obtained, then the signal is reconstructed based on this information. The reconstructed signal is free from noise. If the error between the predicted electrical conductivity from the noisy data and the actual electrical conductivity is sufficiently small, the error between the reconstructed signal and the original signal is also sufficiently small. Since the reconstructed signal is noise-free, the goal of denoising is achieved, as shown in Figures 3.

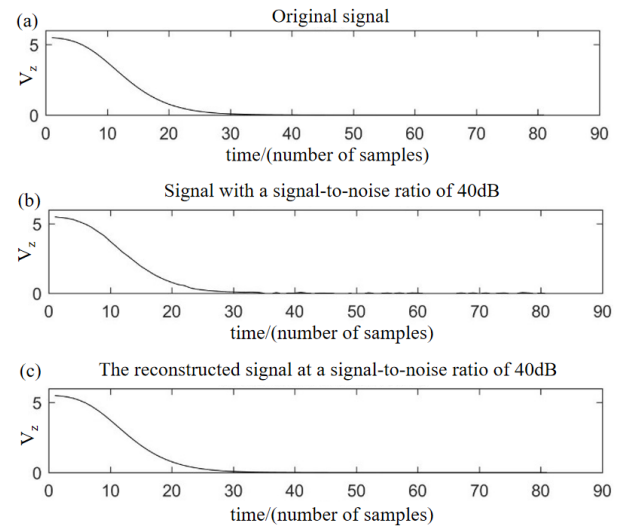


Figure 3. Signals(the response of GATEM) (a) Original signal (b) Signal with a signal-to-noise ratio of 40dB (c) The reconstructed signal at a signal-to-noise ratio of 40dB

The noise-free data composes of the matrix A, and the reconstructed signals composes of the matrix C. Assuming there are n samples and m time points, both A and C are two-dimensional matrices with n rows and m columns, where each row represents an electromotive force signal. The average relative error (ae) can be calculated using the following formula:

$$ae = \left(\sum_{i=1}^n \sum_{j=1}^m \left| \frac{A_{ij} - C_{ij}}{A_{ij}} \right| \right) / (n \times m) \times 100\% \quad (2)$$

In this paper, 100 samples are selected for reconstruction

and there are 81 time points($n = 100, m = 81$). The ae values for different signal-to-noise ratios are as shown in Table 2.

Table 2. ae Values for Different Signal-to-Noise Ratios

SNR	ae
30dB	0.63%
40dB	0.35%
50dB	0.27%
70dB	0.27%

As observed from the table, the error between the denoised signal and the original signal is very small. When the signal-to-noise ratio is above 30dB, the average relative error is not greater than 1%. In this paper, the testing was also conducted with data at a signal-to-noise ratio of 20dB, where some data had larger errors. If we use a criterion of a relative error not exceeding 1%, the accuracy of this network can reach 92%.

4. Conclusion

The GATEM system has been successfully applied in various fields such as groundwater resource exploration and coal resource exploration, yielding promising results. In this paper, based on the methods mentioned above, the following work was conducted to address issues in numerical simulation and noise suppression:

1. Carrying out the parallel computation of GATEM responses based on the OpenMP. The speedup for static scheduling, dynamic scheduling, and heuristic scheduling for a three-layer model is 3.98, 4.28, and 4.64, respectively.

2. Deployed the parallel computing program based on the OpenMP on a cloud computing platform. As the number of computational models increasing, the speedup is also increased, with a maximum speedup reaching 11.37.

3. Employed a neural network approach to reconstruct noisy electromagnetic signals. When the signal-to-noise ratio is above 30dB, the error between the denoised signal and the original signal is very small, with an average relative error not exceeding 1%.

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