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2D Magnetotelluric Inversion based on Deep Learning

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Abstract

Magnetotelluric sounding (MT) is a deep exploration method that inverts and infers the underground resistivity structure by measuring changes in the electromagnetic field of the earth's surface. It is an important method for studying the electrical properties and distribution characteristics of the earth's internal structure and rock formations. At present, typical magnetotelluric inversion methods include Bostick inversion method (Bostick), nonlinear conjugate gradient inversion method (NLCG), Occam inversion method (Occam) and so on. For simpler geoelectric models, the current conventional inversion methods based on the initial uniform half-space model can invert the location and size of anomalies in the geoelectric model. However, the actual geological structure is often more complicated, and conventional magnetotelluric inversion methods are highly diversified. It is often difficult to obtain a true underground model structure by inverting with a uniform half-space or one-dimensional inversion as the initial model. In recent years, neural network technology has been widely used in various fields because of its ability to approximate various end-to-end non-linear mapping relationships. Through deep learning, the electromagnetic observation data and the geoelectric model can be learned, and the mapping of the electromagnetic observation data to the geoelectric model can be established, so as to realize the mapping relationship between the observation data and the geoelectric model.

Keywords

MT; Deep Learning; Inversion; D-Linknet.

1. Related Work

The inverted sample data is used in the magnetotelluric inversion experiment based on deep learning in this article to verify that the method can accurately describe the deep stratum and fault structure with the inversion results. Therefore, the structure of the geoelectric model used in the deep learning constrained inversion experiment data set cannot be too simple. However, the existing measured magnetotelluric data is very valuable and limited, and the field data collection is too difficult. Therefore, the inversion sample data used in this paper refers to the geological data of a small area. In order to obtain enough training sample data, this paper combines the characteristics of the geological structure of this small area to move some of the stratum faults randomly. Although this method cannot completely simulate the actual measured magnetotelluric data, it has certain significance for the study of magnetotelluric restraint inversion methods based on deep learning.

The geoelectric model of the inverted sample data has a mileage of 600km and a depth of 180km. Referring to the geological data of a small area, the established geoelectric model template is shown in Figure 1(a), and the resistivity data of different blocks in the geoelectric model is shown in Figure 1(b):

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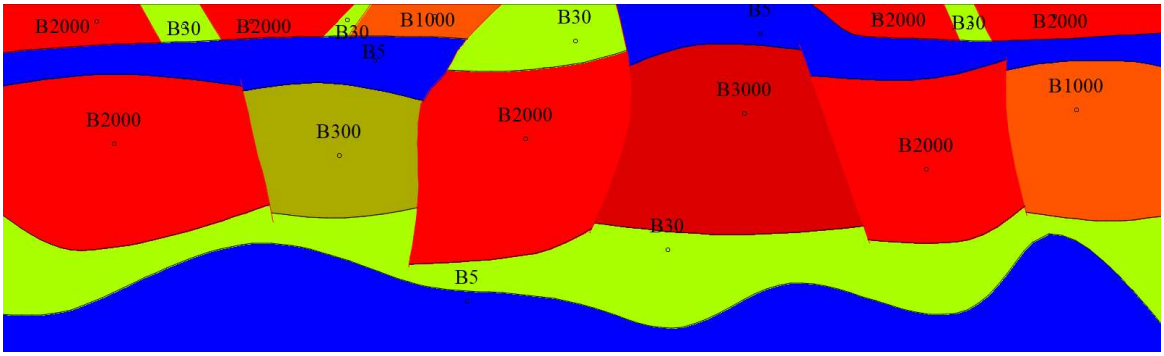

(a)Geoelectric model

1	B100	(255, 255, 0)	100
2	B1000	(255, 85, 0)	1000
3	B2000	(255, 0, 0)	2000
4	B30	(170, 255, 0)	30
5	B300	(170, 170, 0)	300
6	B3000	(220, 0, 0)	3000
7	B4000	(200, 0, 0)	4000
8	B5	(0, 0, 255)	5
9	B50	(112, 173, ...	50
10	B500	(190, 85, 0)	500
11	B5000	(196, 0, 0)	5000

(b)Resistivity table

Figure 1. Schematic diagram of geoelectric model structure

Set observation points on the surface of the model. Observation point No. 1 is located at 0 meters, and observation point No. 121 is located at 600km, with an interval of 5km. There are 121 measuring points; the frequency range is 0.0001~1000Hz, and there are 60 frequency points in total. By randomly moving each stratum in the template geoelectric model, and randomly assigning a value to the stratum, the range is 1-5000, and 50,000 geoelectric model data are obtained. Finally, the traditional finite element method is used to perform forward calculation of these geoelectric models, and the geoelectric model and the forward response size are interpolated to 256x1024, and finally 50,000 sets of sample data sets for neural network training are obtained. Then according to the deep learning data division experience, the 50,000 sets of sample data are randomly divided into training set, validation set and test set according to the ratio of 8:1:1.

2. Neural Network Training for Magnetotelluric Inversion

Based on LinkNet, Zhou L et al. proposed a D-LinkNet network similar in structure to U-Net. The D-LinkNet network adds a hole convolution layer between the encoding module and the decoding module. The introduction of the hole convolution increases the receptive field of the feature map, so as to obtain the feature information farther in the feature map, which just caters to The need for magnetotelluric inversion simulation. The neural network training for magnetotelluric inversion uses the D-LinkNet network structure, uses the Sigmoid activation function, the SmoothL1loss loss function, and the Adam optimizer, and sets the initial learning rate to 0.01. The inversion training sample data set made in the previous article is sent to the Shenzhen Economic Network for training, and the training model loss value decline curve is shown in Figure 2:

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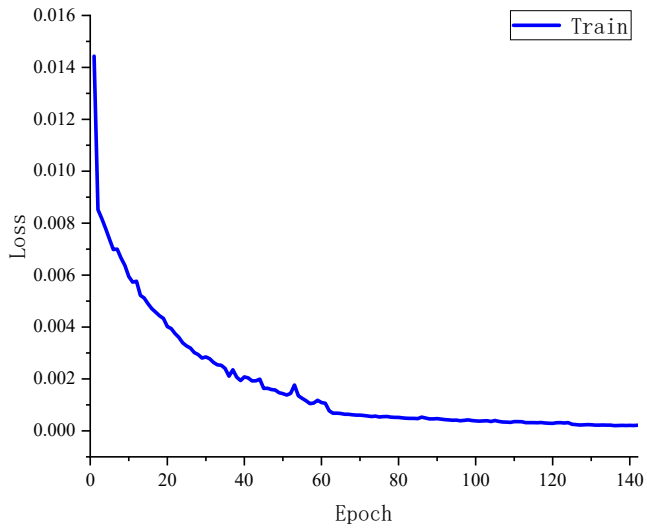
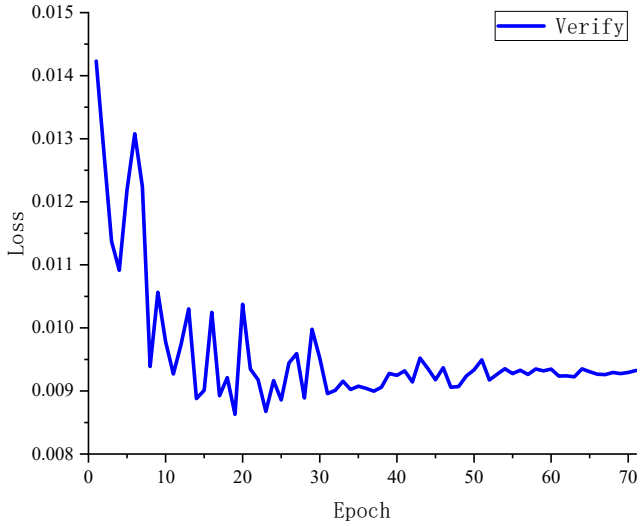


(a)Inversion of network model training curve



(b)Inversion network model verification curve

Figure 2. Inversion of the decline curve of the loss value of the network model

Figure 2(a) shows the loss reduction curve of the neural network model for magnetotelluric inversion. As shown in the figure, the inversion network model reduced the loss value to 1.09E-3 around 60 epochs, and reached 2.15E-4 in 142 epochs. Figure 2(b) shows the reduction curve of the verification loss value of the inversion network model. As shown in the figure, the descending curve of the first 30 epochs showed strong oscillations. After 60 epochs, the loss value began to oscillate stably in a small range, and the training of the inversion network model ended.

3. Magnetotelluric Inversion based on Deep Learning

Randomly select a use case from the test set in the inversion sample data set made in the previous article, combine the forward data of the use case into observation data, and then use the neural network model trained in the previous section to calculate the geoelectric model. Figure 3 (a) shows the theoretical results of the geoelectric model in the use case; Figure 3 (b) shows the inversion results calculated using the traditional nonlinear conjugate gradient inversion method; Figure 3 (c) shows the use case Observation data uses the calculation result of the inversion neural network model:

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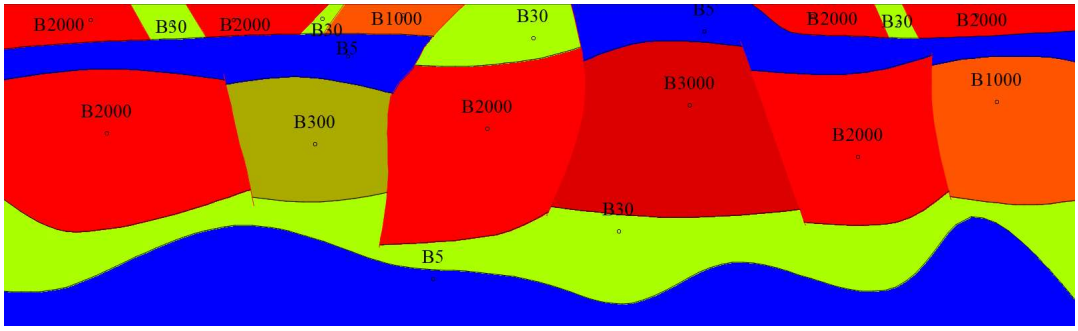
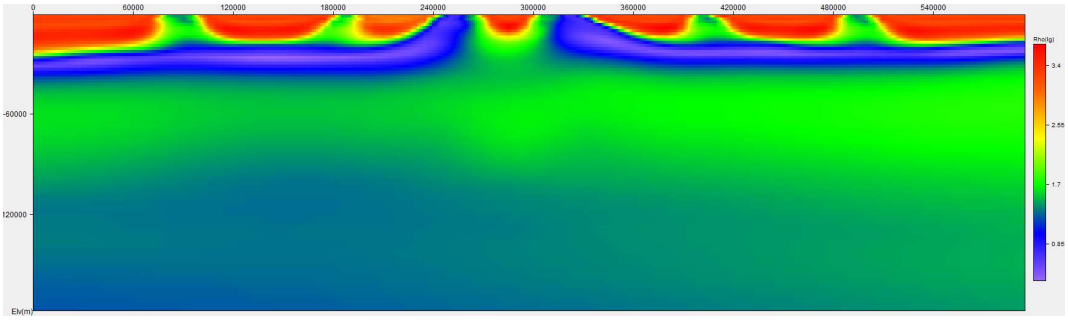
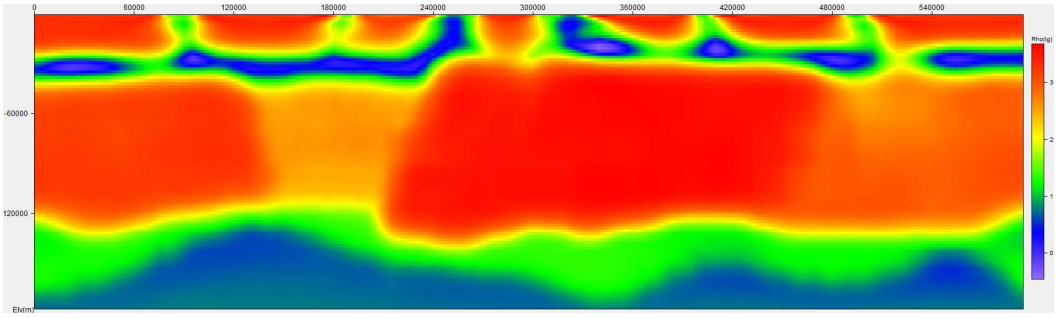


(a)Design model



(b)Nonlinear conjugate gradient inversion results



(c)Inversion results based on deep learning

Figure 3. Comparison of inversion results

As shown in Figure 3, deep learning is used to calculate the inversion geoelectric model of the observation data. The inversion result is highly similar to the initial design model in the model structure, and the formation and fault information are well described. Compared with the inversion results of the traditional nonlinear conjugate gradient inversion method, the magnetotelluric inversion method based on deep learning can better calculate the deep formation information of the geoelectric model. In addition, as a result of the inversion of the magnetotelluric inversion method based on deep learning, the resistivity information of the geological block is also highly similar to the design model.

4. Conclusion

In the inversion calculation in the field of magnetotelluric sounding, with the deepening of the geoelectric model, conventional inversion methods cannot well invert the deep geological structure, which is more difficult for researchers engaged in geological research. . Therefore, this paper uses neural network to train the network model of the non-linear mapping relationship between the observation data and the geoelectric model, which solves the problem of the difficult inversion of complex models of conventional magnetotelluric inversion and the low inversion resolution. Magnetotelluric inversion method based on deep learning can realize the inversion of complex geological models, and the inversion results are far more precise in describing the formations and faults than the inversion results of traditional inversion methods.

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