Inversion of 1D audio magnetotelluric data based on residual convolution neural network

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Abstract. The 18-layer residual convolution neural network (ResNet18) were used for 1D audio magnetotelluric (AMT) data inversion. In order to avoid the dependence of the traditional iterative algorithm on the initial model and calculate sensitivity matrix, we have trained ResNet18 via providing model parameters instantaneously. The residual network was used to solve the problem of deep network gradient disappearing. Deep network and lots of sample data could improve the generalization of the network. The experimental results showed that it could obtain reliable inversion results for synthetic AMT data.

1. Introduction

In recent years, with the successful application of deep learning methods in computer vision, speech recognition and other fields, many geophysical workers had used it for geophysical inversion [1–5]. Compared with traditional artificial neural networks, deep neural networks have more layers. As the network parameters increase, deep neural networks can represent more complex situations, but there are also some shortcomings. Generally speaking, the difficulty of training a deep neural network is mainly due to the obstruction of the gradient backflow. When the gradient is transmitted to the shallower layer, it is already very small, and the perturbation of the shallower weight is small too. To solve this problem, the residual network proposed by He [6], had played an important role in the development of deep learning. This structure solves the problem of gradient disappearance when deep neural networks are being trained. When we are training a deep neural network, a large number of network parameters need to be fitted. At this time, a large number of sample sets were required to prevent overfitting [7]. Overfitting means that the neural network only learned the data in the training set, but did not learn the overall trend.

In summary, due to many advantages over traditional inversion methods, there are more and more applications of deep neural networks in geophysical inversion, but a few people use large sample sets and particularly deep networks for training. To this end, for solving the 1D AMT inversion problem, based on the idea of a residual convolutional neural network, an 18-layer 1D convolutional neural network was built in this paper, and 3 million sample data were used to train the network.

2. Deep learning inversion method

2.1. 1D AMT inversion framework based on deep learning

In this section, the basic framework of the 1D AMT data inversion based on deep learning was described. As shown in Figure 1: the main content can be divided into three parts: 1) Generation sample sets by 1D AMT forward simulation; 2) Creating a deep neural network and training the
network until the training accuracy is reached, then saving the network parameters; 3) Prediction (inversion).

**Figure 1.** 1D AMT data inversion framework based on deep learning

To ensure the accuracy of the data in the sample set, we used the 1D AMT analytical solution to generate the sample set. Each sample consists of 40 model parameters and 40 Kania apparent resistivity responses. Because our sample set had 3 million samples, we only drew 1% of the samples as the validation set, and the remaining 99% of the samples as the training set. We added 0.1%-0.5% Gaussian random noise to the apparent resistivity of the training set and validation set to improve the anti-noise ability of the network. In order to achieve faster convergence when we were training the network, we performed log normalization and Max-Min normalization on the data. Deeper networks usually have better generalization, but are prone to the problem of gradient disappearance. We used the idea of residuals to solve the problem of vanishing gradients, and built an 18-layer fully convolutional neural network. After training the network, we saved the network parameters. During the inversion, we first imported the saved network parameters into the network and then inputted the apparent resistivity into the trained network, which would directly give the model parameters.

### 2.2. Synthetic data inversion

In this part, we tested 4 theoretical models by using the trained network. In order to show the generalization ability of our trained network, the resistivity value of the tested models was completely different from the sample set. For each conductivity model, we compared the inversion results of deep learning and the inversion results of the traditional Gaussian Newton algorithm.

We added 1% Gaussian noise to the apparent resistivity used in the inversion. Figure 2. showed the inversion results of 2-5 layer model. From the inversion results, ResNet18 algorithm and Gauss-Newton algorithm both got better inversion results.
3. Conclusion
Different from traditional iterative inversion methods based on gradient algorithms, this paper studied the application of deep learning method in 1D AMT inversion. The method was mainly divided into three steps: generating a sample set, building and training network, predicting (inversion). The main time was spent on making sample sets and training the network. Once the network was trained, the prediction took almost no time, which was a huge advantage. In order to solve the problem of gradient disappearance when deep networks were being trained, drawing on the idea of a residual convolutional neural network, I built an 18-layer 1D convolutional neural network, using 3 million samples for training. Deep networks and a large amount of sample data made the generalized ability of the trained network stronger. The inversion method based on deep learning could obtain reliable inversion results.

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