Research on the Universality of Convolutional Networks in Resistivity Inversion

Benchao Liu1,2, Qian Guo1,3, Yonghao Pang1,2 and Peng Jiang∗

1Geotechnical and Structural Engineering Research Centre, Shandong University, Jinan, Shandong 250061, China.
2 School of Qilu Transportation, Shandong University, Jinan, Shandong 250061, China.
3 School of Civil Engineering, Shandong University, Jinan, Shandong 250061, China.
Email:sdujump@gmail.com

Abstract. Resistivity inversion, as an important method to study the relationship between geological models and apparent resistivity data, is a typical non-linear problem. Convolutional neural networks have huge advantages in processing complex mapping relationships between images, so they are used to solve resistivity inversion problems. The convolutional neural network's weight sharing greatly improves the learning efficiency of the network, but there is a certain degree of incompatibility between this characteristic and the resistivity data model. In this work, the universality of the method was further verified by designing multiple complex anomalies and different background resistivities. The effectiveness of our proposed method is verified by comparing the inversion effects of different test sets with the results of traditional linear inversion.

1. Introduction
The essence of the resistivity inversion problem is to realize the reconstruction of the true underground geological situation by analyzing the characteristics of the apparent resistivity data. Resistivity inversion method is one of the commonly used exploration techniques, and is widely used in the fields of engineering geological exploration, hydrological environment survey and mining exploration [1-4]. However, resistivity inversion imaging presents highly ill-posed, non-linear and multi-solvant problems. The introduction of deep learning method can realize the analysis, learning and interpretation of various data like human brain, and complete the complex relational mapping by summarizing the law of massive data. In recent years, deep learning has achieved revolutionary results in the fields of computer imaging, speech recognition and natural language processing, and biomedicine, and has become a frontier hotspot of cross-disciplinary research. Deep learning can be understood as a feature learning method that transforms the apparent resistivity data into higher-level expressions through a non-linear model, mining the deep features of the data, and learning the complex mapping relationship between the data and the model to achieve resistivity intelligent inversion. Compared with the traditional method, deep neural network is more efficient and accurate in solving inverse problems [5].

Li et al [6] Applied deep learning to the inversion of seismic data and proposed an end-to-end seismic inversion network (SeisInvNet), which can make full use of all seismic data and solve the discomfort of this traditional seismic inversion problem Qualitative problem. Liu et al (2019) integrated three prior
constraints into the unet convolutional neural network to solve the resistivity inversion problem. Add vertical position information to supplement data location information and improve model resolution. Using deep weighted constraints to redistribute network learning capabilities to improve the inversion results of deep anomalies. A smooth penalty constraint is added to suppress false anomalies. In order to further improve network performance, more and more scholars have begun to focus their research on the network structure itself. The validity of the method is verified by simulation data sets and physical model experiments. In this paper, in order to further study the universality of the variable convolution network, a more complex geological model is designed. We analyze and evaluate the inversion results from two aspects: visualization and error index and verify the superiority of volume adaptive convolutional network in resistivity inversion.

2. Algorithm

2.1. Related concept
As shown in Figure 1, affected by the distribution law of electric field, the apparent resistivity data of the same anomalous body at different depths have different patterns, and the effective feature distribution of the data is also uneven.

In the study of convolutional neural networks, the problem of the size of the effective receptive field\cite{7} is a problem that cannot be ignored. In a receptive field, all pixels have different degrees of influence on the output result. As shown in the figure, in each apparent resistivity profile, the valid data is local, and its distribution is affected by the size and location of the abnormal body.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure1.png}
\caption{Apparent resistivity profiles of anomalous bodies at different depths}
\end{figure}

2.2. Database establishment
In this work, about 13,000 sets of numerical simulation data bureaus were designed. The complexity of the data set is mainly reflected in two aspects. The first is the increase in the number of anomalies. The types of anomalies are still different combinations of high-resistance anomalies and low-resistance anomalies. The resistivity values are 10Ωm, 30Ωm, 800Ωm, and 1000Ωm, respectively. The second difference is that the background resistivity is layered, with a lower layer resistivity value of 300Ωm and a deep layer resistivity value of 500Ωm. We randomly divide the data set into a training set, a validation set, and a test set according to a ratio of 10: 1: 1.

Each set of data sets includes a model and results for apparent resistivity. By establishing an automatic modeling loop system to ensure the quantity and diversity of the data set, the apparent resistivity data is realized using finite element forward modeling, using the Wenner-Schlumberger device.

2.3. Inversion results
Figure 2 shows the inversion results of the adaptive convolutional network for different numbers of anomalies. With the increase of the number of anomalous bodies, the inversion accuracy of the network decreases, but the distribution of underground anomalous bodies can be basically described. Through the third model case, it can be concluded that the neural network algorithm can accurately distinguish different resistivity worthy of high resistance anomalies.
In the third example, we designed two anomalous bodies with different resistivity values that are worthy of high resistance. From the inversion results, we can see that the neural network can accurately capture and distinguish different anomalous bodies with different resistivity values. In the fourth example, the inversion accuracy of the neural network algorithm for the same type of abnormal body is verified. When all abnormal bodies are high-resistance abnormal bodies, the neural network can still perform high-quality imaging. From the inversion results of the last example, it can be seen that when multiple different types of anomalies exist, the neural network still has a good response to the anomalies below the low-resistance body, which is completely superior to the traditional inversion algorithm.

![Figure 2](image1.png)

**Figure 2.** Inversion results for different numbers of anomalous bodies

![Figure 3](image2.png)

**Figure 3.** Inversion results under different background resistivities

To further study the universality of convolutional networks, we designed a non-layered background resistivity. Figure 3 shows three typical calculation examples. The first is that the three anomalies are
all on the same background resistivity and are near the boundary. The model examples of the intermediate design are anomalous bodies distributed in different background resistivities. The final designed model has one anomaly in each of the two layers of background resistivity, and one anomaly exists in both layers of background resistivity. From the inversion results of the three examples, it can be seen that the resistivity intelligent inversion algorithm based on the convolutional neural network has good adaptability to different background resistivities.

In Figure 4, we show the loss curves of the inversion results on the training and validation sets. It can be seen from the downward trend of the two curves that there is no overfitting during the training process. After 500 epoch trainings, the error dropped from 0.03 to less than 0.005, and the curve gradually converged.

![Loss curves of convolutional neural network on training and validation sets.](image)

**Figure 4.** Loss curves of convolutional neural network on training and validation sets.

In addition, we performed a comparative analysis with traditional linear inversion algorithms. In Figure 5, from top to bottom are the resistivity model, the traditional linear inversion results, and the convolutional nerve inversion results. The traditional linear inversion results are obtained by using Swedish high-density software RES2DINV[8], which can use two-dimensional electronic imaging for geological interpretation in more complicated geological regions. Both algorithms can reflect the layered effect of the background resistivity, but the layered interface of the convolutional neural network is clearer. For shallow high-resistance bodies, the traditional linear inversion algorithm can capture the position of the anomalous body and the resistivity value, but the shape description is not accurate enough. For low-level low-resistance anomalies, the inversion results of the convolutional neural network are significantly better than traditional linear inversion algorithms.
3. Conclusions
The non-linear problem of resistivity inversion has always been a research hotspot. Deep learning is an important means to achieve complex mapping between data because it can summarize laws based on massive data. The inversion process of inferring a geological model by analyzing the characteristics of apparent resistivity data can be regarded as a mapping between images. The local receptive field and weight sharing characteristics of convolutional neural networks have made important achievements in identifying images. Different from ordinary images, the resistivity data has the characteristics of depth variation due to the influence of the electric field distribution law.

In this paper, in order to further verify the universality of the method, a variety of complex geological models are designed. It can be seen from the inversion results that as the number of abnormal bodies increases, the inversion accuracy of the neural network decreases, but high-quality imaging can still be achieved. After adding a layered model, the inversion results will not be affected. From the qualitative and quantitative evaluations in this paper, the inversion results of this method are far superior to the traditional methods.
References

[1] Chambers J E, Kuras O and Meldrum P I 2006 Electrical resistivity tomography applied to geologic, hydrogeologic, and engineering investigations at a former waste-disposal site *Geophysics* **71**(6) B231-B239.

[2] Chambers J E, Wilkinson P B and Wardrop D 2012 Bedrock detection beneath river terrace deposits using three-dimensional electrical resistivity tomography *Geomorphology* **177** 17-25.

[3] Feng R, Li X Q and Tao Y L 1997 Resistivity imaging in hydrogeological exploration *Acta Seismologica Sinica (in Chinese)* **19**(6) 655-663.

[4] Wilson S R, Ingham M and McConchie J A 2006 The applicability of earth resistivity methods for saline interface definition *Journal of hydrology* **316**(1-4) 301-312.

[5] Fan K, Wei Q and Carin L 2017 An inner-loop free solution to inverse problems using deep neural networks *Advances in Neural Information Processing Systems* 2370-2380.

[6] Li S, Liu B and Ren Y 2019 Deep learning inversion of seismic data *arXiv preprint arXiv* **1901**.07733.

[7] Luo W, Li Y, Urtasun R., and Zemel R 2017 Understanding the effective receptive field in deep convolutional neural networks *arXiv preprint arXiv* **1701**.04128.

[8] Loke M 1996 “Res2dinv, rapid 2d resistivity inversion using the least-squares method” *Software distributed by Iris Instruments, Orleans, France.*