Physics-Driven Deep Learning Inversion for Direct Current Resistivity Survey Data

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Abstract—The direct-current (dc) resistivity method is a commonly used geophysical technique for surveying adverse geological conditions. The resistivity model can be reconstructed from data by inversion, which is an important step in geophysical surveys. However, the inversion problem is a serious one that can easily lead to incorrect results. Deep learning (DL) provides new avenues for solving inverse problems, and these methods have been widely studied. Currently, most DL inversion methods for resistivity are purely data-driven and depend heavily on labels (real resistivity models). However, real resistivity models are difficult to obtain through field surveys. As an inversion network may not be effectively trained without labels, we built an unsupervised learning resistivity inversion scheme based on the physical law of electric field propagation. First, a forward modeling process was embedded into the network training to convert the predicted resistivity model to predicted data, and form a data misfit with the observation data. Unsupervised training independent of labels was realized using the data misfit as a loss function. Moreover, a dynamic smoothing constraint was imposed on the loss function to alleviate the ill-posed inverse problem. Finally, a transfer learning scheme was employed to adapt the network trained with simulated data to field data. Numerical simulations and field tests showed that the proposed method can accurately locate and depict geological targets.

Index Terms—Direct-current (dc) resistivity inversion, engineering verification, physical laws, transfer learning, unsupervised deep learning (DL).

I. INTRODUCTION

The direct-current (dc) resistivity method, which is characterized by low economic cost, high survey efficiency, and strong sensitivity to water-bearing structures, is one of the most commonly used solutions for geophysical surveys [1], [2]. Therefore, it has been widely used for various purposes, including traffic engineering [3], [4], [5], dam surveys [6], [7], and environmental engineering [8], [9]. An effective inversion method is the key to improving the reliability of imaging techniques. Currently, linear inversion is the main method for inverting real-world data, and it predicts models according to the physical laws of geoelectric fields. However, the inversion results are highly dependent on the initial model and only a locally optimal solution is usually obtained using this method. Moreover, imaging results usually contain artifacts that influence the geological interpretation of the results.

Using nonlinear inversion methods can mitigate such problems because of their strong global search capacity. A number of studies have focused on applying nonlinear inversion methods to invert dc resistivity data and obtain globally optimal solutions, including the use of genetic algorithms [10], ant colony algorithms [11], and simulated annealing algorithms [12]. However, these methods have not been widely adopted for inverting real-world data because of low computational efficiency. In contrast, neural network methods are relatively fast and enable well-fitted nonlinear mapping between input data (potential or apparent resistivity) and output data (resistivity model) by extracting information from large training sample sets [13], [14], [15]. These methods are only time-consuming during training, and the trained networks have an extremely high inversion efficiency when performing inferences, which makes them suitable for resistivity surveys. In recent years, with the significant optimization of artificial intelligence algorithms and computing performance, an upgraded version of neural networks, namely, deep learning (DL), has developed rapidly [16], [17], [18]. DL has a greater ability to construct complex nonlinear mappings than older neural network methods. Thus, solving geophysical inversion problems using DL has gradually become a research hotspot [19], [20], [21], [22], [23], [24]. Currently, research on DL inversions of real-world data from electrical surveys is still in the exploratory stage. Liu et al. [25] studied DL inversion using convolutional neural networks (CNNs) for resistivity survey data. In this study, depth weighting and smoothing constraints are added to the loss function to alleviate ill-posed inverse problems. For synthetic data, the neural network achieves better inversion results than traditional linear inversion and does not involve linearization theory. Based on this, a variable convolution kernel is used to adapt the apparent resistivity image features, which further improves the imaging performance of complex models [26]. For example, Aleardi et al. [27] combined CNN inversion...
with a Monte Carlo simulation framework to estimate model uncertainty caused by noisy data; and Vu and Jardani [28] extended the DL inversion method to 3-D surface survey imaging.

Currently, most DL-based resistivity inversions are purely data-driven and trained in a supervised manner, which makes their performance heavily dependent on an extensive training set. This poses two challenges when applying these methods to real-world data. First, resistivity model information corresponding to real geological models is difficult to collect, which increases the difficulty of supervised training with real-world data and corresponding models. A commonly used solution is to train networks with a synthetic dataset and fine-tune them with a few field samples to adapt them to real scenarios; this method is called transfer learning. Second, even for synthetic datasets, the resistivity model covering generic realistic exploration scenarios should be massive and exhaustive. However, because of limitations in time and computing resources, this type of synthetic dataset is difficult to generate. Deep neural networks trained only by a dataset with insufficient samples may not be able to accurately approximate nonlinear mapping between survey data and resistivity models. In other words, the networks may not comply with the physical laws of inversion (e.g., electric field propagation). Therefore, DL based on physical laws is more promising for the inversion of dc resistivity data. This idea has been adopted for seismic inversion problems [29], such as those outlined by Jin et al. [30], who embedded a forward modeling module at the end of a neural network to form a data misfit and realize unsupervised learning. In addition, Colombo et al. [31] applied unsupervised learning inversion to transient electromagnetics and obtained high-resolution resistivity models for synthetic and field data; while Liu et al. [32] incorporated the physical laws of magnetotelluric wave propagation into a purely data-driven DL approach and successfully applied this method to field data.

To the best of our knowledge, an unsupervised DL method based on physical laws has not been previously reported for dc resistivity data inversions. This novel method driven by physical laws is expected to have promising applications for resistivity survey data. However, three crucial issues related to using physics-driven unsupervised DL for dc resistivity inversion must be resolved.

1) How can the laws governing electric field propagation be adopted in deep neural networks to achieve unsupervised learning?

2) How can prior information constraints be used to ensure the convergence of the network training process?

3) How can the method be applied to field data when the size of the real-world training dataset is too small to support network training?

In this study, to address the first problem listed earlier, we constructed a physics-driven resistivity data inversion network (PhResNet) that combines the architectures of widely used CNNs and fully connected neural networks (FCNNs). In this network, the forward operator simulating electric field propagation is applied to the inversion architecture, which helps guide the network training by fitting the forward results of the predicted model with the survey data. On this basis, the second problem listed earlier is solved by imposing a dynamic smoothness constraint on the loss function. Finally, the third problem is addressed by the proposed transfer-learning method, i.e., PhResNet, which can be applied to a small amount of resistivity survey data. PhResNet was successfully applied to real-world data collected during an advanced tunnel survey, and the inversion results for the field tests matched the excavation disclosures, thus validating the feasibility and effectiveness of PhResNet.

Major contributions of this work include the following.
1) Forward modeling to characterize physical rules was embedded into the network training, and data misfit was used as a loss function.
2) Several variants of the network architecture were designed to fit various data forms under different electrode configurations.
3) DL inversion was successfully applied to field data using a transfer learning method.

II. METHODOLOGY

In this section, we present a PhResNet. First, we designed the overall network architecture to enable unsupervised learning. Subsequently, we designed two specific encoders for different types of dc resistivity data. To obtain an effective inverse network, we proposed a dynamic smoothing constraint to guarantee training convergence. Finally, we improved the transfer learning method by applying unsupervised inversion to real-world data.

A. Overall Architecture of PhResNet

The objective of this study was to achieve unsupervised learning by introducing physical laws. The goal was to eliminate the dependence on labels (resistivity model) and improve the generalizability of the inversion network. For dc inversion, the physical law is represented by an electric field distribution that obeys Poisson’s equation. Forward modeling can transform a geoelectric model into observational data using Poisson’s equation and boundary conditions. Therefore, forward modeling was added to the neural network as an effective method of introducing the physical laws of electric field propagation. Self-supervised learning using only resistivity data is a common unsupervised learning methods [33]. In this method, forward modeling enables the mapping to proceed from the output model to the data. We used data misfit as the loss function after the predicted model was mapped to the data. The advantage is that the training process using this loss function does not require labels. Based on the above-mentioned analysis, forward modeling was added to the network. Finally, a large number of samples were used to train the network parameters through the loss function for the network to fully learn the physical laws.

The training sample set included N groups of resistivity models $m_{i}^{\text{label}}$ ($i \in N$) and their corresponding survey data $d_{i}^{\text{obs}}$ ($i \in N$). The neural network parameters were represented as $w$. The purpose of the inversion network was to construct a mapping $F$ of $d_{i}^{\text{obs}}$ to $m_{i}^{\text{label}}$ by training $w$

$$F(d_{i}^{\text{obs}}, w) \rightarrow m_{i}.$$  

(1)

A typical supervised learning pipeline is illustrated in Fig. 1. The resistivity model and survey data were used as the input information for the neural network. The loss function was set to the residuals of the predicted model $m_{i}^{\text{pred}}$ and the
The governing equation for the propagation of the electric field is shown as [34]

$$-\nabla \frac{\nabla \Phi(x, y, z)}{\rho(x, y, z)} = -2I\delta(x-x_0)\delta(y-y_0)\delta(z-z_0). \quad (2)$$

Equation (2) is the Poisson equation derived from Ohm’s law and the conservation of current, which governs the relationship between electrical resistivity $\rho$ and potential $\Phi$. $I$ is the current in amperes, and $(x_0, y_0, z_0)$ are the coordinates of the point source of the injected charge. $\delta()$ represents the Dirac delta function.

The potential is solved using a resistivity model, governing equations, and boundary conditions. This process is called forward modeling in dc resistivity surveys. We applied the finite element method to solve the forward model discretely because the finite element method is more accurate than the finite difference method in dealing with nonuniform continuum and complex shapes.

In this section, data feature extraction methods are proposed to adapt to various electrode configurations in dc resistivity surveys; additionally, data from different electrode configurations have different array forms. Data can be roughly classified into image and nonimage data. For example, the apparent resistivity of surface surveys is image data, and the potential surveyed in holes is nonimage data.

1) PhResNet-i for Image Data: Image data have a spatial correspondence with the resistivity model [25], which is suitable for feature extraction using CNNs. U-Net architecture based on CNNs has good localization and feature representation capabilities [35]. Therefore, we used U-Net to extract features from image data. U-Net is usually composed of two parts: an encoder and a decoder. In particular, shallow features (encoder part) and deep features (decoder part) are jointly used for inversion using the shortcut (skip connection). The physics-driven resistivity inversion network of the image data (PhResNet-i) is shown in Fig. 3. The details of each layer of UNet in this study are listed in Table I. First, the network parameters were initialized randomly. Subsequently, multiple apparent resistivity image data were simultaneously fed into the encoder network to extract features through batch processing. A predicted model corresponding to the input data was generated by the decoder network. Furthermore, the predicted data were computed using a forward modeling. Finally, the average gradients of the multiple models were computed using the loss function. This model gradient was back-propagated along the red line to update all network parameters.

2) PhResNet-n for Nonimage Data: It is difficult to construct spatial correspondence with the resistivity model for nonimage data; therefore, CNNs are unsuitable for nonimage data. An FCNN can be used to extract features from nonimage data, although its fully connected neurons will result in a large number of parameters and affect the training efficiency. Drawing on the method of splitting data by shot points in seismic DL inversion [36], we attempted to split the nonimage data (potential) according to current electrodes. Each split dataset was processed using the same network parameters to reduce the total network parameters. In most cases, nonimage data have a specific fixed structure or pattern. However, we can reconstruct the resistivity model using encoder–decoder networks without providing spatial correspondence. The encoder can compress raw data into a feature map (2-D feature field) with a smaller amount of data, while the decoder reconstructs the feature map into a resistivity model. We enforce each split data to learn a feature map corresponding to the entire resistivity model regardless of the actual relationship between each split data and resistivity model. After training, the information in each feature map will be spatially aligned with the resistivity model. Reconstructing the resistivity model with CNNs is beneficial. Therefore, the FCNN in the encoder establishes the spatial correspondence between the original data and resistivity model and extracts high-level features for reconstruction. Since each split dataset has its own sensitive region, the feature maps of different split data will contribute towards reconstructing different parts of the resistivity model. However, unlike seismic survey data (time series), each dc resistivity survey data point usually corresponds to four
electrodes (two current electrodes and two potential electrodes), i.e., each datum contains the information of four electrodes with thousands of location data. However, the network cannot easily learn such large amounts of data. As shown in Fig. 4, we attempted to address this problem by implementing the following measures.

1) The location information was supplemented by the apparent resistivity data. As shown in the left column of Fig. 4, the input data constituted a collection of potential and apparent resistivity data. Apparent resistivity data incorporating geometric factors carried spatial information, which was beneficial for reducing the neural network’s search range for the solution. Note that both apparent resistivity and potential data were used as inputs to the neural network, whereas only one type of data is used as input for traditional methods. Because the values of apparent and potential resistivity are significantly different, two network input paths were constructed.

2) Inversion networks distinguish data powered by different holes by grouping them. As shown in the left column of Fig. 4, the data for the two holes are divided into two parts. The data split by the current electrode needed to be split twice according to the position of the borehole where the current electrode was located because the values and trends of the data were similar when the current electrode was located in the same borehole. For the groups with current electrodes that were not in the same borehole, the data values and trends were considerably different. Therefore, the data from different boreholes were not processed using the same network parameters.

3) Extracted neighborhood information was used to compensate for information lost after grouping. The features between different sets of data were ignored after the split operation was performed. To solve this problem, the split data were sorted according to the current electrode’s spatial order. The difference in electric fields between adjacent groups was generated by moving the current electrode. This difference in electric field was regarded as neighborhood information. As shown below the middle column of Fig. 4, we extracted this neighborhood information.
TABLE I

| Block | Type   | Filter | stride | Input | channel |
|-------|--------|--------|--------|-------|---------|
| B0    | Upsample \ / \ / | Data |         | 9     |         |
| B1    | Conv   | 3x3x3  | 1      | B0_out | 32      |
|       | MaxPool | 1x2x2  | 0      |        | 32      |
| B2    | Conv   | 3x3x3  | 1      | B1_out | 32      |
|       | MaxPool | 2x2x2  | 0      |        | 64      |
| B3    | Conv   | 3x3x3  | 1      | B2_out | 128     |
|       | MaxPool | 1x2x2  | 0      |        | 128     |
| B4    | Conv   | 3x3x3  | 1      | B3_out | 256     |
|       | MaxPool | 2x2x2  | 0      |        | 256     |
| B5    | Conv   | 3x3x3  | 1      | B4_out | 512     |
| B6    | Conv/Transpose | 3x3x3 | 2      | B5_out | 512     |
| B7    | Conv   | 3x3x3  | 1      | B6_out | 512     |
| B8    | Conv/Transpose | 3x3x3 | 1, 2, 2| B7_out | 256     |
| B9    | Conv   | 3x3x3  | 1      | B8_out | 256     |
| B10   | Conv/Transpose | 3x3x3 | 2      | B9_out | 128     |
| B11   | Conv   | 3x3x3  | 1      | B10_out| 128     |
| B12   | Conv/Transpose | 3x3x3 | 1, 2, 2| B11_out| 64      |
| B13   | Conv   | 3x3x3  | 1      | B12_out| 64      |
| B14   | Conv   | 3x3x3  | 1      | B13_out| 32      |
| B15   | Upsample \ / \ / |        |         | B14_out| 1       |

information using three convolution layers to provide more effective information at the network input.

By combining the measures listed earlier, an encoder network for nonimage data was designed, as shown in Fig. 4. Based on cross-hole electrical resistance tomography, the two boreholes were numbered #1 and #2, respectively. Electrodes were placed in the boreholes and used either as current or potential electrodes. Neighborhood information was then extracted from the apparent resistivity data. Furthermore, merged data were obtained by splicing the neighborhood information and potential data. Finally, a feature map proportional to the size of the resistivity model was generated after incorporating the fused data into the FCNN. In the synthetic inversion test, the output sizes of the FCNN were 2048, 1024, 512, 128, and 128 in sequence. The view function was used to transform the compression vector of the two holes into a feature map with a size of 8 × 16. Feature maps contain both low- and high-dimensional data features, and these features were used to directly obtain the predicted model by inputting the feature map into the CNNs. The physically driven resistivity inversion network for nonimage data (PhResNet-n) developed in this study is shown in Fig. 5. The main difference between PhResNet-n and PhResNet-i is the use of an FCNN-based encoder network instead of a U-Net architecture. The two network architectures implemented the inversion of image/nonimage data, which means that DL methods are no longer limited to electrode configurations.

C. Gradient Calculation Based on the Dynamic Smooth Constraint

Drawing from traditional linear inversion, a smoothness constraint was added to the loss function to ensure that the network training process converged. The loss function of PhResNet includes a data term and a model term, as follows:

\[
\text{Loss} = (f(m) - d^{\text{obs}})^T (f(m) - d^{\text{obs}}) + \lambda(\delta^n_m)^T(\delta^n_m).
\]

(3)

where \( f(m) \) represents forward modeling mapping; \( m \) is the predicted model; \( \lambda \) is a regularization factor that balances the data and model terms; and \( n \) is usually 1 or 2. The model gradients were solved using the Gauss–Newton method for the above-mentioned equations

\[
\delta m = (J^TJ + \lambda C^TC)^{-1}J^T(f(m) - d^{\text{obs}}).
\]

(4)

where \( J \) is the Jacobian matrix and \( C \) is the smooth constraint matrix.

Smooth constraints are double-edged swords; weak constraints may not guarantee convergence in the inversion process, while strong constraints, which may alleviate the multisolution problem of inversion, may produce predicted models that are too smooth and incapable of accurately reflecting abnormal areas. To solve this problem, we attempted to use a gradient-calculation strategy with dynamic-smoothness constraints. In the early stage of network training, the gradient calculation process was unstable because the predicted model was noticeably different from the label. Therefore, the smoothness constraint was enhanced by a larger regularization factor, namely, \( \lambda \). Furthermore, the influence of smooth constraints was reduced in late training to achieve accurate imaging of the target regions. The dynamic regularization factor calculation formula is as follows:

\[
\lambda = \lambda_0 \times (1.0 - \text{epoch}/\text{max_epoch})^\mu
\]

(5)

where \( \lambda_0 \) is the initial value, \( \text{max_epoch} \) is the maximum number of training times, and \( \mu \) is the rate of change factor.

D. Transfer Learning

In a real resistivity survey, the amount of dc resistivity survey data cannot meet the requirements of network training. Transfer learning is a common method in DL to solve this issue. Thus, we attempted to devise a new transfer learning method suitable for a small amount of dc resistivity survey data. The network parameters trained by the synthetic samples were used as the starting point of the transfer learning.
process, which was followed by fine-tuning a part of the network parameters with a small number of real samples. Two popular methods for transfer learning are available: 1) full fine-tuning, i.e., updating the parameters for all layers of the network and 2) linear probing, i.e., retraining the last linear layer. Full fine-tuning can improve the feature extraction of pre-trained networks using real-world data but may distort pre-training features. When the pre-training features are good and the distribution shift is large, linear probing may obtain better migration effect than full fine-tuning. Linear probing directly inherits the feature extraction method of synthetic data. By randomly initializing the last linear layer, it is possible to jump out of the starting point of the pre-trained network model. However, linear exploration alone may not be effectively applied to real-world data. Therefore, we devised a transfer learning strategy that combines the advantages of full fine-tuning and linear probing, and a schematic of this strategy is shown in Fig. 6. First, the pre-trained network was linearly explored using real-world data to expand the search for solutions. Second, the network was fully fine-tuned to improve feature extraction from real-world data. Finally, the network was iteratively trained and inverted on the new inputs (target data) multiple times until reaching a set number of times or achieving a convergence value. The proposed transfer learning strategy had two positive outcomes: 1) the network parameters were further adjusted to better adapt to the target data and 2) the optimized network was able to generate more accurate resistivity models.

III. SYNTHETIC INVERSION TESTS

In this section, we compare the proposed PhResNet with traditional linear inversion methods using numerical tests. We did not perform comparisons with other DL methods because they all require supervised training using real resistivity models.

A. Training Details

We employed the SGD (Ruder S, 2016) optimizer with a momentum parameter of 0.9 and a weight decay of $1e^{-4}$ to update all parameters of the network. The initial learning rate was set to $0.2e^{-4}$. The size of the minibatch was set to 8. During the network training, dropout techniques were used to avoid overfitting the training data. Network training was implemented using Pytorch on a desktop system (Intel(R) Xeon(R) Gold6148 CPU @2.40 GHz, 512 GB RAM, GPU: NVIDIA TITAN RTX). This configuration was used for all the tests conducted in this study.

B. 3-D Surface ERT

A synthetic dataset for a 3-D surface survey was built using random disturbance and discrete combinations. The
inversion area consisted of a grid of $2 \times 2 \times 2$ m, with a range of $16$ m($X$) $\times 66$ m($Y$) $\times 16.5$ m($Z$). Four survey lines were placed at a distance of 4 m from each other. In total, 128 electrode points, each separated by 2 m, were used. The background resistivity of the resistivity model was $1000 \, \Omega \cdot m$. Fig. 7 shows the possible shapes of the low-resistance target from the slice map. Its resistivity was $20 \, \Omega \cdot m$. To obtain sufficient information, we used electrode configurations, including the Wenner–Schlumberger, dipole–dipole, and pole–dipole configurations. The dataset contained a total of 4626 resistivity models and was divided into training, validation, and test sets in a ratio of 10:1:1.

In Fig. 8, we show the loss curve of PhResNet-i on the training and validation sets. Both loss curves decrease gradually with increasing epochs. Therefore, overfitting is not observed in training. As the loss of the training set contains model items, its value is slightly larger than the loss of the verification set.

The inversion results are shown in Fig. 9, and they consist of three parts, i.e., real resistivity model, predicted model, and slice map. The predicted model obtained using the linear approach showed only one target. This finding may be related to the stronger signal of the shallow target relative to that of the deep target, which caused the deep signal to be masked. PhResNet-i has strong information mining ability and can extract information effectively from weaker signals. Consequently, both targets could be described and differentiated. The resistivity value of the target area was close to the actual value.

C. 2-D Cross-Hole ERT

Similar to that described in Section III-B, a synthetic dataset for a 2-D cross-hole ERT was built. The inversion area consisted of a grid of $1 \times 1$ m, with a range of 16 m($X$) $\times 32$ m($Z$). Two survey lines were placed 14 m apart. A total of 64 electrode points with a spacing of 1 m were used. The background resistivity of the resistivity model was $200 \, \Omega \cdot m$. Fig. 10 shows the possible shapes of the low-resistance target. Its resistivity was $20 \, \Omega \cdot m$. To obtain sufficient information, we used the following electrode configurations: bipole–bipole, dipole–dipole, and pole–pole. Potential and apparent resistivity data were obtained using forward modeling. The dataset contained 4880 resistivity models and was divided into training, validation, and test sets according in the ratio 10:1:1.

In Fig. 11, we show the loss curves of PhResNet-n on the training and validation sets. It is difficult to train nonimage data. In the process of obtaining feature extraction capability, the PhResNet-n encountered some difficulties, which showed that the loss curve of the verification set fluctuated greatly. On the whole, the loss curve decreases gradually as the epochs increase.

The cross-hole survey data were processed using PhResNet-n because they contained nonimage data. Fig. 12 shows the inversion results for two low-resistivity targets.
that were close to each other. Horizontal resolution using cross-hole ERT is generally poor. When the horizontal distance between two targets at the same depth is small, the imaging results of the two targets can be easily combined using linear inversion. The unsupervised inversion network PhResNet-n had a prior distribution because it was trained using a large number of samples. PhResNet-n can accurately discriminate between image’s multiple objects. As shown in Fig. 12, the results obtained using PhResNet-n were close to the those obtained using the actual model in terms of size, shape, and resistivity values.

IV. MODEL TEST

Unsupervised learning inversion was applied to real-world data using the transfer learning method described in Section II-D. The specific process is presented as follows. The modeling parameters were determined according to the electrode coordinates, electrode configurations, and detection requirements. Training datasets with large amounts of synthetic data were constructed based on the geology and potential anomalies of the surveyed area. ResinvNet was pre-trained on synthetic datasets to obtain inversion capabilities for synthetic data. Subsequently, the network was retrained using the actual data from the previous stage. Finally, the trained PhResNet was applied to the new data. The final resistivity model was generated after multiple iterations.

A. Data Preparation

We designed a model test to invert low-resistivity anomalies using cross-hole ERT. The low-resistivity body is designed to be the simplest block rather than a complex shape. The application of unsupervised learning inversion to real-world data is still at the exploratory stage. One or two abnormal bodies were designed. The ratio of geometric factors in the model to the engineering prototype was 1:20. A comparison of geometric factors is presented in Table II.

The model design is shown in Fig. 13(a), and corresponding photographs are shown in Fig. 13(b). The survey area was 0.8 m (length) × 0.8 m (width) × 1.6 m (depth), and it was connected to the ground on all four sides, which helped mitigate the boundary effects on the electrical tests. Four survey lines were arranged in the survey area. A total of 4 × 16 electrodes were used, with a spacing of 0.1 m on the same survey line. For better coupling, the electrodes were packed with wet clay. In addition, the survey area was filled with fine-grained soil. The background resistivity ranged from 200 to 400 Ω·m.

Clay, salt, and water were used to simulate anomalous bodies. The size of each abnormal body was 0.2 × 0.1 × 0.1 m, and the resistivity value was maintained at 20–50 Ω·m by controlling the material ratio. The final imaging area consisted of the two diagonal faces of the survey area (#1–#3 and #2–#4). Fifty sets of survey data were collected by placing the anomalous bodies horizontally or vertically at different depths. A photograph of the test process is presented in Fig. 14.

B. Results

The imaging results obtained using unsupervised learning inversion and linear inversion are shown in Fig. 15. The black lines on both sides are the survey lines (located at X = 0 m and X = 1.15 m). The black dots on the measurement line
Fig. 15. Comparison of the inversion results using different models. (a) Unsupervised learning inversion (PhResNet-n) and (b) linear inversion.

represent the electrodes, and the white dotted box indicates the actual location of the anomalous body. The results of the linear inversion showed that it could not differentiate between the two anomalies. However, PhResNet-n effectively located and imaged the two abnormal bodies with an error of only 0.1 m, and these imaging results were relatively close to those obtained using the real model.

V. FIELD SURVEY

We conducted a field-test application study to verify the effectiveness of the unsupervised learning inversion method for practical engineering.

A. Engineering Overview and Detection Scheme

The survey area was located in a water diversion project in Northwest China. The tunnel was excavated using the drill-and-blast method, and the survey site in the tunnel was located at the bottom of the river. The top of the tunnel was approximately 271 m from the riverbed. Many faults are observed in this area, and groundwater is recharged by rivers. Therefore, the area is prone to water inrush disasters during tunnel excavation. Water flow was observed in an advanced borehole located 12 m in front of the survey site, and the flow rate reached 1300 m$^3$/h. This water may have originated from fissure water because the surrounding rock was intact. The water gushing speed decreased after full curtain grouting. After the slurry solidified, the tunnel continued to be excavated to the survey site. We performed cross-hole ERT using probe holes to identify potentially adverse geological conditions.

A schematic of the advanced survey is shown in Fig. 16. The tunnel face was 7.8 × 7.8 m. Probe holes were placed in the corners to increase the imaging range. The distances in the horizontal and vertical directions of the probe holes were 5.0 and 4.0 m, respectively. The probe holes were named H1–H4 in a clockwise direction. A total of 16 × 4 electrodes were used, with a spacing of 1.0 m. The survey lines penetrated the probe hole using a PVC tube.

B. Inversion and Excavation Results

The noise level of the data was high owing to the complex tunnel environment. Therefore, the smooth constraint had a high regularization factor value to guarantee convergence. The inversion results are shown in Fig. 17. In the range of 0–8 m, the resistivity value of the geological body was high but lower than the normal resistivity value of dry rock. The corresponding excavation site is shown in Fig. 18(a). The surrounding rock in this area was wet. We speculate that the area was filled with water in the early stage but the hidden danger of the water effluent was eliminated after grouting treatment. In the range of 8–10 m, distinct low-resistivity regions are observed in both imaging results (H1–H3 and H2–H4). A small fault was discovered at this location during an earlier investigation, and it was then treated using approximately 150 t of grouting. Therefore, we speculate that fissure water still exists at this location. The corresponding excavation site is shown in Fig. 18(b). We observed consolidated slurry and fissure water, which is consistent with the inversion results. An obvious low-resistivity anomaly was not observed at 10–16 m. The
area was excavated later, and water flow from the site was not observed. It should be noted that the effect of transfer learning is limited because of the lack of data in the early stages of the project. This rendered the unsupervised inversion network insufficient for processing real-world data. In addition, owing to the high level of data noise, the imaging resolution was low. Therefore, the inversion result could only roughly reflect the range of the abnormal body but could not image the body in detail.

VI. CONCLUSION

In this study, we developed a new inversion method based on unsupervised learning to process dc resistivity survey data. This method uses a data misfit as a loss function to guide inversion network training by embedding physical rules (of forward modeling) into the network structure. In addition, a dynamic smoothness constraint was added to the loss function to stabilize the training process. Based on this, a transfer learning method was proposed to improve the ability of the inversion network to deal with complex realistic exploration scenarios. The results of the numerical simulations and model tests demonstrate that unsupervised learning inversion can accurately reconstruct nonlinear mapping from the input (potential or apparent resistivity) to the output (resistivity model).

Compared with existing DL-based resistivity inversion methods, the proposed method eliminates the dependence of real resistivity models on the training set. Because of the difficulty in obtaining a real resistivity models, this method is more suitable for real survey scenarios. Compared to the traditional linear method, the proposed method has two advantages: 1) the inversion time of the trained network is only 1 s, and this efficient processing speed can satisfy engineering requirements, especially for large-scale surveys and 2) has a strong global search capacity and does not rely on the initial model. However, because of the limited number of studies, it is too early to conclude that unsupervised learning inversion is superior to traditional linear methods. Furthermore, network training requires millions or even billions of forward models, whereas the linear method only requires dozens of forward models. Such an efficiency disadvantage can be mitigated using computer hardware and algorithms.

Real survey data need to be accumulated for future studies. However, the effect of transfer learning was improved by building a high-quality sample library. Based on the real data example, we can state this conclusion.

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