TRANSFER LEARNING SEISMIC IMPEDANCE INVERSION METHOD BASED ON TEMPORAL CONVOLUTIONAL NETWORKS

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ABSTRACT

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The nonlinear mapping between seismic data and impedance can be established by Temporal Convolutional Networks (TCN), which has been proved by forward modeling data. However, whether the deep neural network can be used to train an inversion mapping model with good generalization ability under a small number of labeled samples remains to be explored. In view of this, the noise analysis of the TCN seismic impedance inversion method was firstly carried out, and the model test showed that the TCN seismic impedance inversion method had certain noise resistance. Secondly, an inversion mapping model was obtained based on the training of Marmousi-2 data set, and then five traces of Overthrust model samples were added for fine-tuning to obtain a new inversion mapping model. The inversion of Overthrust was performed based on the TCN transfer learning inversion mapping model. And the model test results showed that: with a small number of labels, the inversion results of the Overthrust dataset based on TCN transfer learning are higher than the Pearson sum determination results obtained by TCN inversion, and the error profile is relatively small compared to the true impedance. Furthermore, TCN transfer learning method ,which was effectively proved in adjacent blocks of the actual data, compared with the result of the TCN inversion. Therefore, the introduction of transfer learning in TCN seismic impedance inversion can improve the generalization ability of the inversion mapping model trained with a few labeled samples in practical application.

KEY WORDS: temporal convolutional network, transfer learning, fine-tuning, seismic impedance inversion.

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INTRODUCTION

Deep learning technology has been widely applied in image (Cao et al., 2016), voice (Hou et al., 2017) and computer vision (Lu and Zhang, 2016), etc. The successful application of the above scenarios provides ideas for intelligent geophysical inversion (Song et al., 2021; Zhang et al., 2021; Shao et al., 2022).

At present, Convolutional Neural Networks (CNN) (Lecun and Bottou, 1998) and Recurrent Neural Network (RNN) (Zaremba et al., 2014), which are the two main categories of deep learning algorithms, can be used for seismic inversion (He and Wang, 2021; Li et al., 2020). Das et al. (2019) obtained inversion mapping model by one-dimensional CNN, and Guo et al. (2019) used RNN [Bidirectional Short and Long Time Memory Network (BILSTM)] for seismic impedance inversion. In addition, Alfarraj and Alregib (2019) proposed to apply the C-RNN model, which is integrated CNN with RNN. And the results showed that the combination of CNN and RNN can obtain better inversion results. In recent years, various inversion methods based on convolutional networks have emerged in an endless succession. Wu et al. (2020) used Fully Convolution Neural network (FCN) (Long et al., 2015) and transfer learning (Yosinski et al., 2014; Tzeng et al., 2014, 2017), to carry out the seismic impedance inversion in different geological features of the actual seismic data. Generative Adversarial Networks (GAN) are used to achieve semi-supervised seismic impedance inversion (Wu et al., 2021).

With the further study of deep learning in seismic inversion, Bai et al. (2018) proposed TCN by combining the advantages of CNN and RNN, which is superior to RNN in various time series modeling tasks (Hochreiter and Schmidhuber, 1997; Pascanu et al., 2013). According to the test of Marmousi-2 model (Martin et al., 2006), TCN has certain advantages in seismic impedance inversion (Mustafa et al., 2019), which proves that TCN can obtain better inversion results by seismic impedance inversion of data with the same data characteristics. However, it has not been confirmed whether this method has certain anti-noise performance (Richardson and Feller, 2019; Huang et al., 2020) or whether the inversion mapping model trained under a small number of labeled samples is effective. In view of this, the author introduces the strategy of transfer learning (Zhuang et al., 2015) on the basis of predecessors and proposes a seismic impedance inversion method based on TCN transfer learning. The verification of this method mainly includes four stages. First, noise analysis is carried out on TCN seismic impedance inversion. It is proved that TCN can effectively establish the mapping relationship between seismic data and impedance and has a certain anti-noise property. Secondly, the pre-trained inversion mapping model is obtained by training the Marmousi-2 model. The pre-trained inversion mapping model can effectively predict the impedance of the data with the same characteristics. And the inversion effect is not good when it is directly used as the inversion mapping model with different data characteristics. Thirdly, five traces of Overthrust (Liu et al., 2004) samples were added to the pre-training inversion mapping model for retraining and fine-tuning to obtain the TCN transfer learning inversion mapping model.

And then seismic impedance inversion was performed for the Overthrust model based on the above seismic mapping model. Finally, the inversion results of TCN transfer learning were compared with the inversion results, which of the 5 traces of the Overthrust data directly by the pre-training model in the second step above, obtained by TCN training. The results showed that: TCN transfer learning seismic impedance inversion method is used to invert the seismic impedance of small dataset training with different data characteristics. And the predicted impedance is closer to the labeled impedance. We also know that its related evaluation index is improved to a certain extent, and it has a certain anti-noise property. TCN transfer learning inversion has achieved certain effect in model testing. The TCN transfer learning seismic impedance inversion method is further applied to the actual data. From the results, this method mentioned above has certain application value in seismic impedance inversion in the small training dataset with different data characteristics.

TCN TRANSFER LEARNING SEISMIC IMPEDANCE INVERSION

TCN seismic impedance inversion can be used to directly learn the complex mapping between seismic data and impedance, which can be used to convert the inversion task into time series modeling. But samples of TCN seismic impedance inversion is less, limitations in the process of practical seismic exploration is larger, on the basis of the author in TCN seismic impedance inversion on the basis of introducing the migration study was carried out on the adjacent region of seismic data inversion, below the structure of the TCN, inversion principle, migration strategy and the inversion process of TCN transfer learning.

Structure of TCN

TCN is a time series prediction network framework proposed by Bai et al. (2018), which has been widely used in sequence script recognition (Lecun and Bottou, 1998), increment problem (Hochreiter and Schmidhuber, 1997), Nottingham Music (Pascanu et al., 2013) and other tasks. TCN combines extended convolution and causal convolution, which can extract feature information across time. It is a deep neural network for time series modeling. Such as Fig. 1(a) is the expansion coefficient of 1, 2, 4, the expansion of the convolution kernel size is 2 causal convolution structure diagram, its network receptive field depends on the depth of the network, and the size of the convolution kernels, and the expansion coefficient, in order to further deepen the network depth and improve the generalization ability of network model to study temporal information, TCN using residual module instead of the convolution layer. To sum up, TCN network is formed by stacking a series of residual blocks in the application of various time series modeling problems [Fig. 1(c)]. The residual blocks have the same structure and are encapsulated by extended causal convolution, the WeightNorm unit, the ReLU unit and the Dropout unit. The schematic diagram is shown in Fig. 1(b). The expansion of the receptive field in TCN depends on the network depth, and the residual structure can well suppress the problem of gradient disappearance or explosion caused by the increase of network layer, and the introduction of extended causal convolution makes TCN more advantageous in time series modeling tasks. In view of this, TCN has the following advantages in time sequence modeling: (1) it has the capability of parallel computing, that is, the mapping of each moment can be calculated simultaneously, and there is a causal relationship between network layers, so there will not be "missed connection" information; (2) TCN is an adaptive architecture, that is, it can be flexibly adjusted to any length, and can obtain sequences of any length and map them to output sequences of the same length; (3) Not only inherits the advantages of RNN in natural language processing to maintain long-term memory, but also through the introduction of causality and expansion convolution, it can maintain longer memory than RNN, and requires less memory, but has a more stable gradient and a more flexible receptive field.

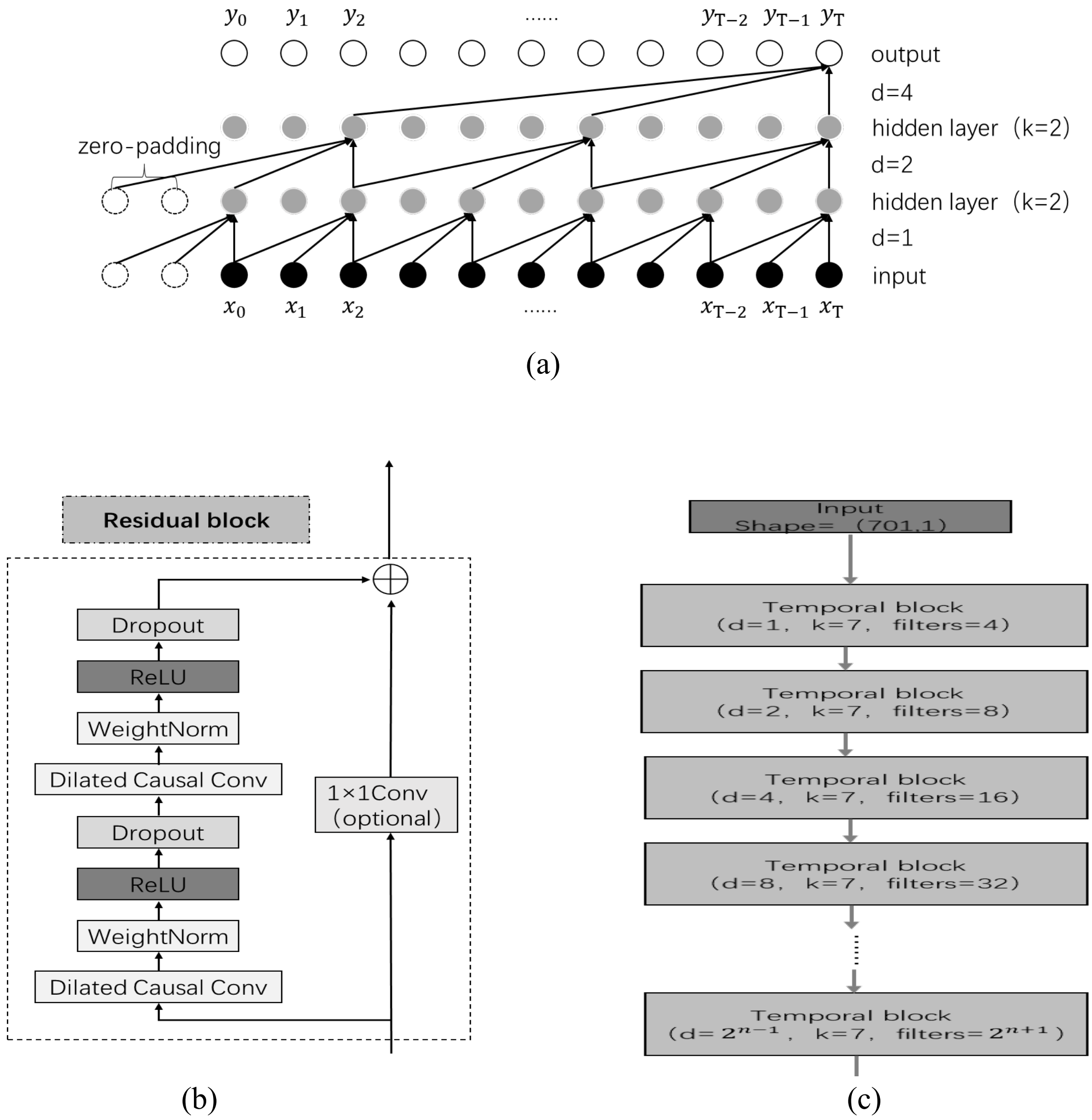


Fig. 1. TCN network structure. (a) Dilated causal conv structure. (b) TCN residual structure. (c) TCN residual stacked structure.

TCN seismic impedance inversion principle

Make $S=\{s_1,s_2,L\ ,s_n\}$ is seismic records, where s_i is trace number i of the seismic record, $P=\{p_1,p_2,L\ ,p_n\}$ is a corresponding record of impedance will first S a subset of the input to the TCN after pretreatment, after prior to transmission, get forecast impedance values of $P_\theta(s_i)$, and calculate the prediction between impedance and the real impedance values of loss function value, and then used to calculate the gradient, In addition, gradient is applied to TCN inversion mapping model to update parameter θ iteratively through back propagation. The loss function value can be minimized by repeating the above process. This process can be called parameter optimization process, and the corresponding mathematical expression is as follows:

$$\theta^{I+1}=\theta^{I}-\eta\cdot\nabla_\theta L(\theta^{I}) \quad , \tag{1}$$

$$\theta^{\wedge}=\arg\min\frac{1}{N}\sum_{n=1}^{N}L(p_i,\ P_\theta(x_i)) \quad , \tag{2}$$

where θ^{I+1}, θ^{I} and θ are the set of weight value w and bias term b, generation I refers to the number of current iterations, η is the learning rate, and $\nabla_\theta L(\theta)$ is the gradient of loss function calculated according to parameters. L represents the loss value between predicted impedance and true impedance, N represents the number of seismic tracks in a subset of S, p_i represents the impedance data model, and $P_\theta(s_i)$ is the predicted value propagated forward through TCN. For end-to-end TCN seismic impedance inversion, the target loss function is the Mean Square Error (MSE) loss function:

$$L=MSE=\frac{1}{n}\sum(p_i-\hat{p}_i)^2 \quad , \tag{3}$$

where n is the number of samples, $\hat{p}_i$ is the predicted value of seismic impedance, and p_i is the true value of seismic impedance. With the decrease of the loss value L, the inversion mapping results tend to be stable and converge at last.

TCN transfer learning strategy and inversion process

Conventional machine learning method to follow the training and prediction of data must be in the same feature space and distribution, and need to have a large number of labeled samples, and migration study is to use existing knowledge to solve the problems of the different but related areas of a machine learning method, mainly using the similarity between the data and the field, Make reasonable use of the knowledge learned before (Yosinski et al., 2014; Tzeng et al., 2014, 2017). Transfer learning has relaxed the two basic assumptions in machine learning. Based on existing knowledge, this method solves the learning problem of only a small amount of data with labeled samples in the target field, or even no labeled samples (Zhuang et al., 2015). The purpose of introducing transfer learning into TCN seismic impedance inversion is also to solve the TCN seismic impedance inversion problem of a small number of labeled sample seismic data with different data characteristics (Fig. 2). The realization process is to first train the seismic data in feature block 1 to obtain a pre-trained TCN inversion mapping model. Further, on the basis of the above pre-trained TCN inversion mapping model, a small number of labeled samples of feature block 2 are added for retraining and fine-tuning to obtain the TCN transfer learning inversion mapping model, and then the data of feature block 2 are inverted. The specific workflow is as follows: In the first step, a large number of labeled samples in block 1 were preprocessed, including noise analysis, normalization and random allocation of input sequence, etc. Secondly, a TCN seismic impedance inversion network is constructed, as shown in Fig. 1(c). The third step is the training of the pre-training inversion mapping model. The samples processed in block 1 are input to the TCN inversion network, and the training network obtains the pre-training inversion mapping model. In the fourth step, transfer learning is carried out, pre-training inversion mapping model is loaded, and a small number of labeled samples in block 2 are input into TCN inversion network for retraining, so as to fine-tune the pre-trained inversion mapping model and obtain the INVERSION mapping model of TCN transfer learning. Finally, seismic data of block 2 are input into TCN transfer learning inversion mapping model to obtain impedance, and the specific implementation process is shown in Fig. 3.

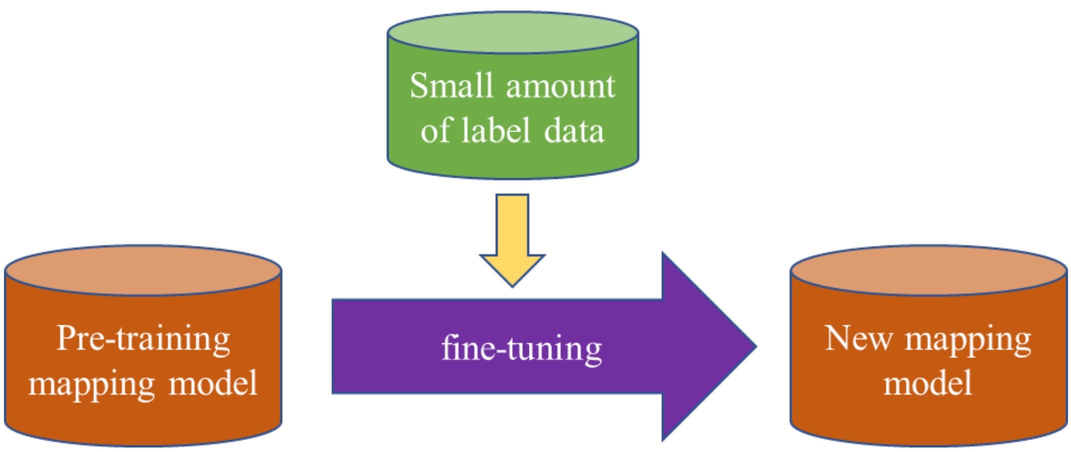


Fig. 2. Implementation pattern of transfer learning.

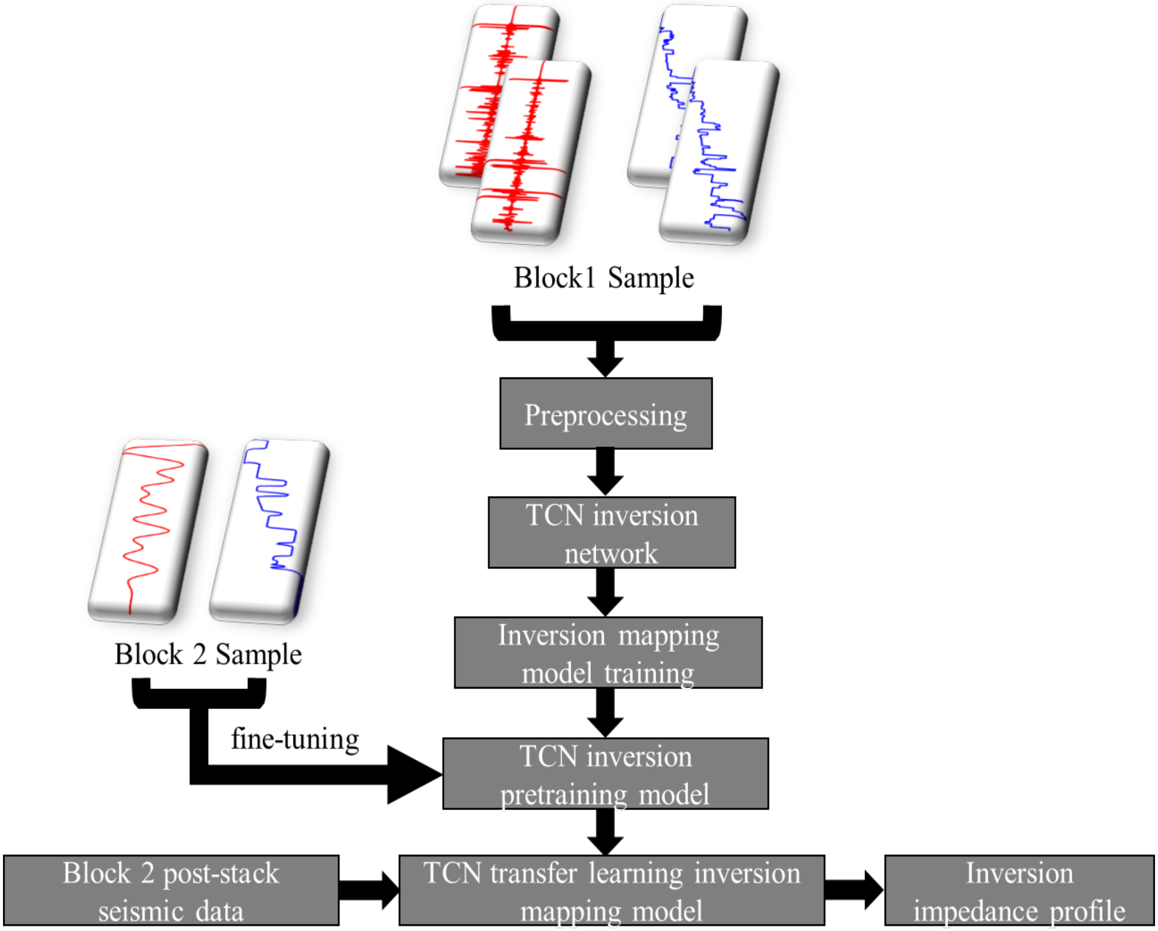


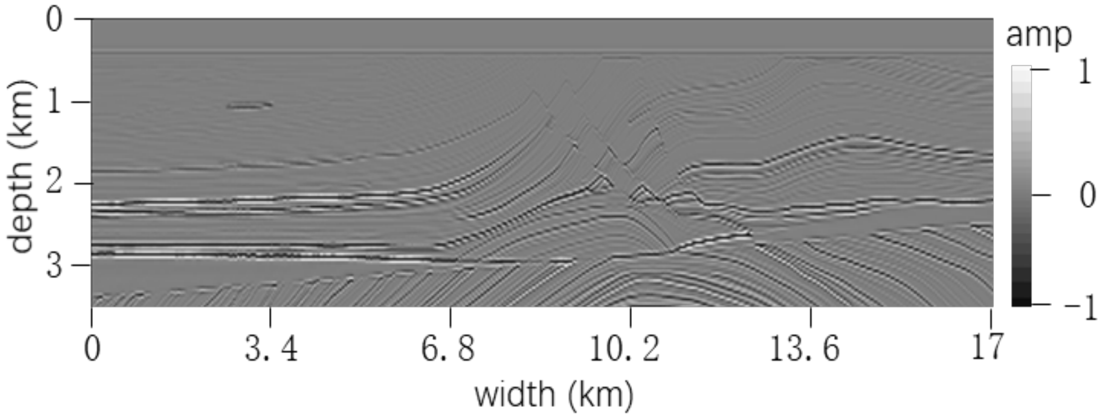
Fig. 3. Implementation process of TCN transfer learning seismic impedance inversion.

FORWARD DATA TESTING

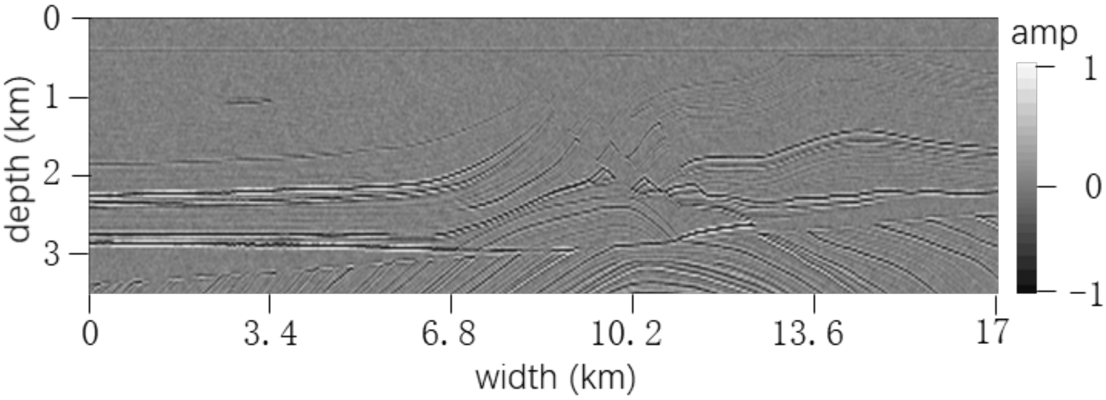
The data to be tested were open data set Marmousi-2 and Overthrust model. Firstly, seismic impedance inversion was performed on Marmousi-2 data using TCN inversion method to prove the effectiveness of TCN seismic impedance inversion method. On this basis, the impedance inversion of Overthrust model by TCN transfer learning was performed, and the inversion results were compared with other inversion results.

Anti-noise test of TCN seismic impedance inversion

In order to prove the anti-noise performance of TCN seismic impedance method, inversion tests were performed on Marmousi-2 model before and after noise addition (Fig. 4).



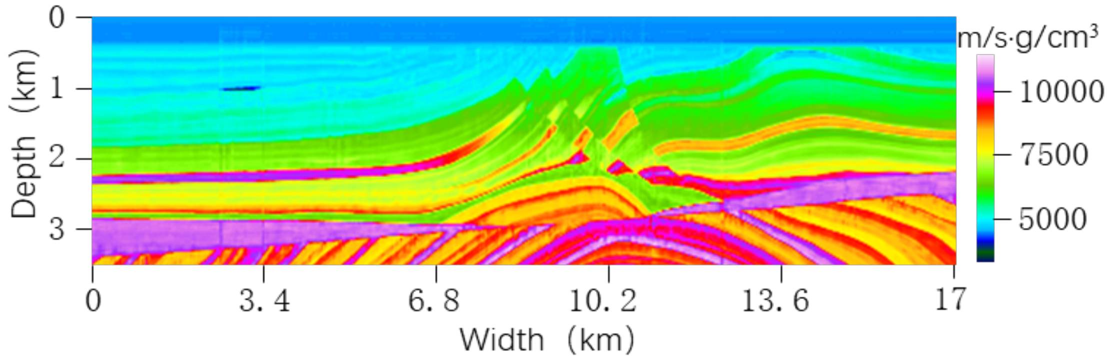
(a)



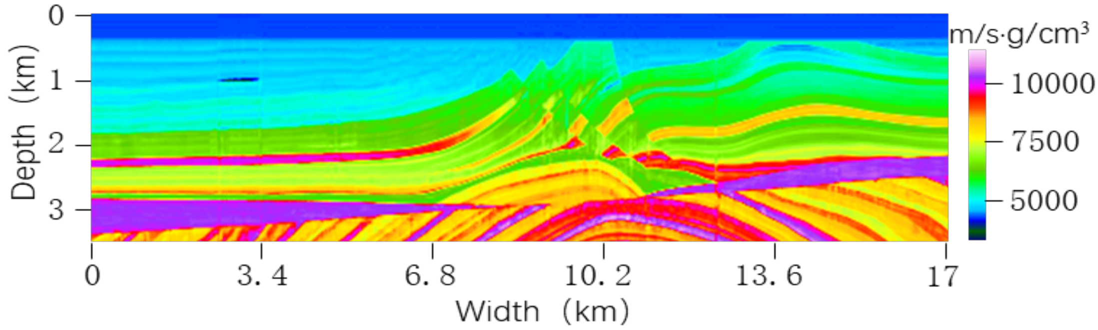
(b)

Fig. 4. Seismic profile of Marmoris-2. (a) Noiseless seismic profile. (b) 20% noisy seismic profile.

The test constructed the training set, verification set and test set in a ratio of about 1:1:4. 450 channels of samples were used as the training set to train the TCN inversion mapping model, and 450 channels were used as the verification set for internal parameter tuning to preliminarily evaluate the generalization ability of the TCN inversion mapping model. In addition, 1821 channels were used as the test set. Used to evaluate the ultimate generalization capability of the inversion mapping model. By testing the Marmousi-2 model before and after adding noise, its TCN inversion profiles are shown in Figs. 5(a), 5(b), 5(c) and 5(d), where 5(c) and 5(d) are the error profiles of inversion results respectively. The experimental analysis before and after adding noise shows that the TCN seismic impedance inversion method can obtain good results in the data containing noise, which shows that the TCN inversion method has a certain anti-noise ability, and lays a foundation for its further application.



(a)



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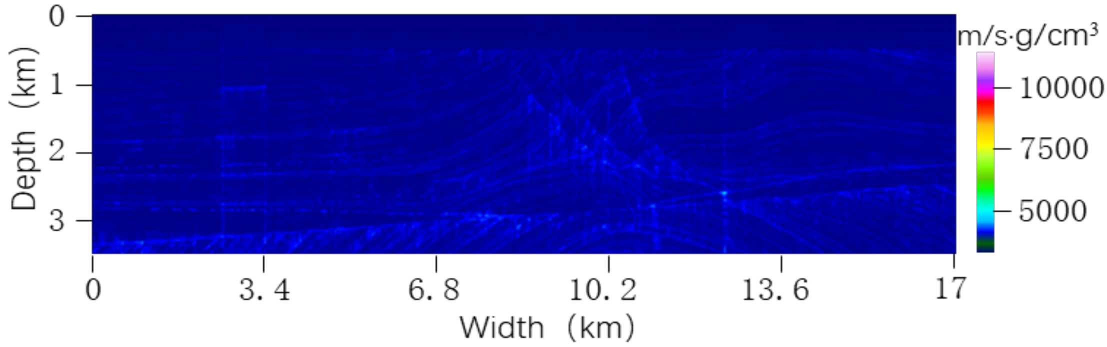
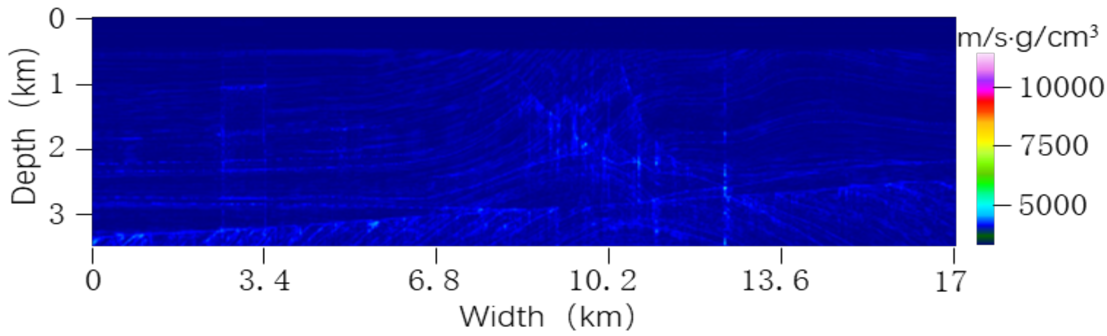


(c)



(d)

Fig. 5. Inversion results of Marmousi-2 model. (a) Noiseless model inversion profile. (b) 20% noise inversion profile. (c) Noiseless model inversion error. (d) 20% noise inversion error.

TCN transfer learning seismic impedance inversion experiment

The model test results show that TCN seismic impedance inversion method can effectively establish the mapping relationship between seismic and impedance, and has a certain anti-noise performance. In order to prove the feasibility of TCN transfer learning seismic impedance method, the Marmousi-2 model was further trained to obtain the pre-trained TCN inversion mapping model. On the basis of the pre-trained TCN inversion mapping model, five Overthrust model samples were added to fine-tune the TCN transfer learning inversion mapping model. Inversion of the Overthrust model (Fig. 6) using the seismic impedance inversion mapping model showed that the inversion results of different methods were different (Fig. 7 and Fig. 8), and the inversion results of TCN migration learning were better than those of other non-migration learning methods (Fig. 8). In order to further quantitatively analyze the inversion results, Pearson Correlation Coefficient (PCC) and Coefficient of determination (r^2) are introduced to evaluate the inversion results. The mathematical formula is as follows:

$$PCC = \frac{1}{N}\frac{1}{\sigma_{\mathrm{p}}\sigma_{\hat{\mathrm{p}}}}\sum_{\mathrm{n}=1}^{N}(\mathrm{p(n)}-\mu_{\mathrm{p}})(\hat{\mathrm{p}}\mathrm{(n)}-\mu_{\hat{\mathrm{p}}}) \quad , \tag{5}$$

$$\mathrm{r}^2 = 1 - \frac{\sum_{\mathrm{n}=1}^{N}[\mathrm{p(n)}-\hat{\mathrm{p}}\mathrm{(n)}]^2}{\sum_{\mathrm{n}=1}^{N}[\mathrm{p(n)}-\mu_{\mathrm{p}}]^2} \quad . \tag{6}$$

Assume p indicates the seismic impedance label, $\hat{p}$ indicates the predicted seismic impedance, and N indicates the number of samples. σ and μ indicate the standard deviation and mean of the seismic impedance, respectively. The larger the absolute value of Pearson coefficient is, the predicted impedance is closer to the real impedance, and the determination coefficient is a measure of the goodness of fit between seismic tracks. The larger the determination coefficient is, the more similar the overall trend is. In this test, Pearson's coefficient, determination coefficient and loss values of some methods under three inversion methods are given respectively, as shown in Table 1. The results show that The PCC and r^2 values of TCN transfer learning inversion are the highest, and the convergence loss of TCN transfer learning inversion on Overthrust model is smaller than that of TCN direct inversion, indicating that TCN transfer learning inversion mapping model has strong generalization ability.

Table 1. Related evaluation indicators.

The evaluation index Inversion method	PCC/%	r^2/%	Convergence loss
Pre-trained inversion mapping model for direct prediction	8.31	0.69	
TCN direct inversion	97.19	94.47	0.019556
TCN transfer learning inversion	97.96	95.97	0.001082

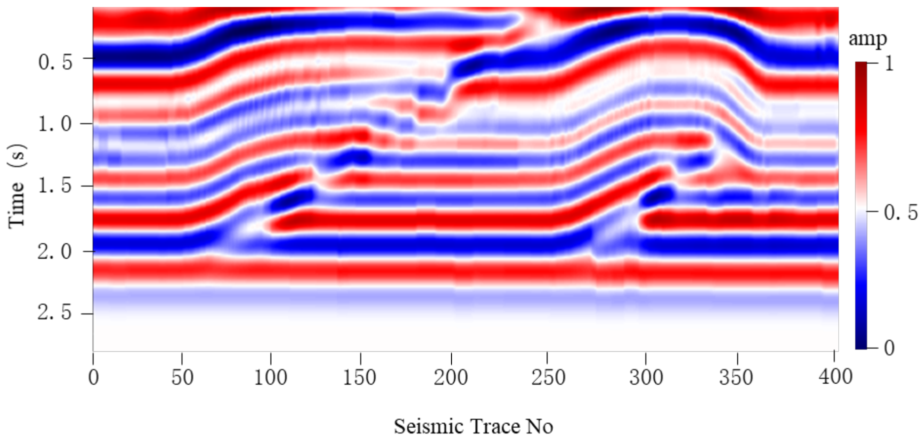
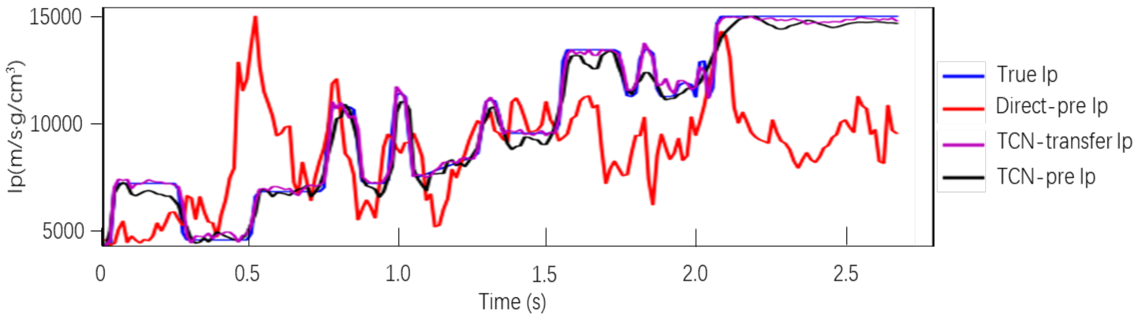
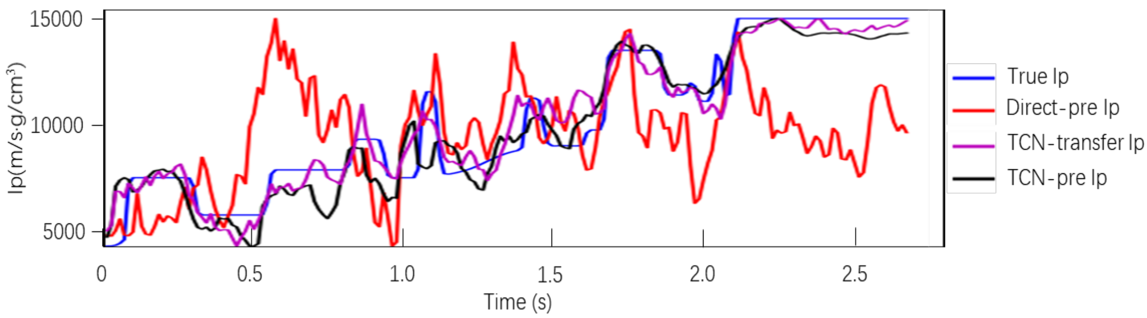


Fig. 6. Seismic profile of the Overthrust model.



(a)



(b)

Fig. 7. Single-channel impedance. (a) Channel 70 impedance. (b) Channel 350 impedance.

THE PRACTICAL APPLICATION

In order to verify the applicability of the study of seismic impedance inversion method based on TCN migration, the author uses the actual data of adjacent region, the main lithology is sand mudstone, in which area A with more well data, the use of the data set to train the inversion mapping model, and select adjacent area B data in data set for fine-tuning the inversion mapping model in section A, Then the fine-tuned inversion mapping model is used to predict the B region. As can be seen from Fig. 9(a) inversion profile in the B area, TCN migration learning inversion results are in good agreement with logging impedance curves [Figs. 9(b) and 9(c)]. Therefore, this method has certain application value to seismic impedance inversion of a few labeled samples.

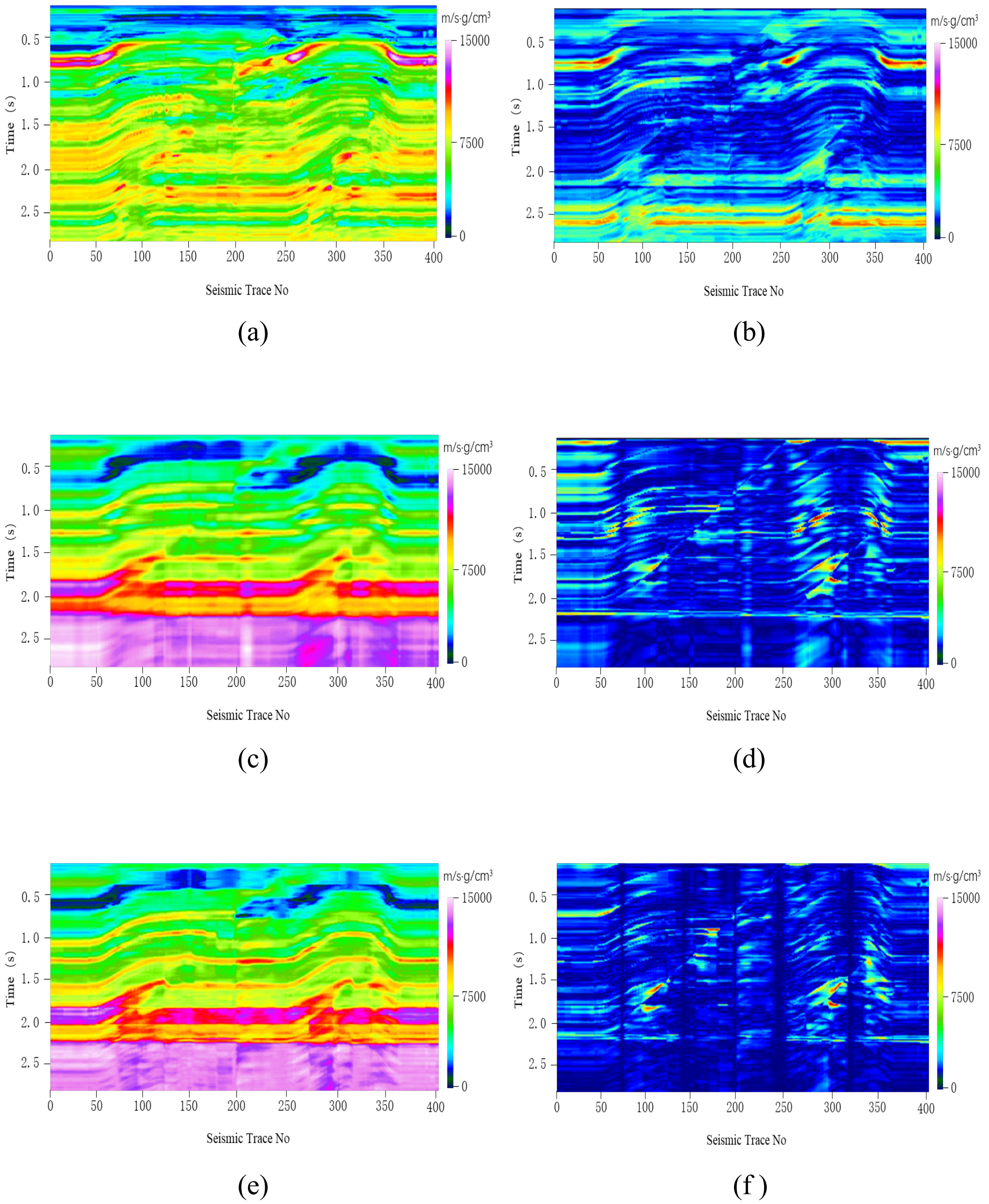
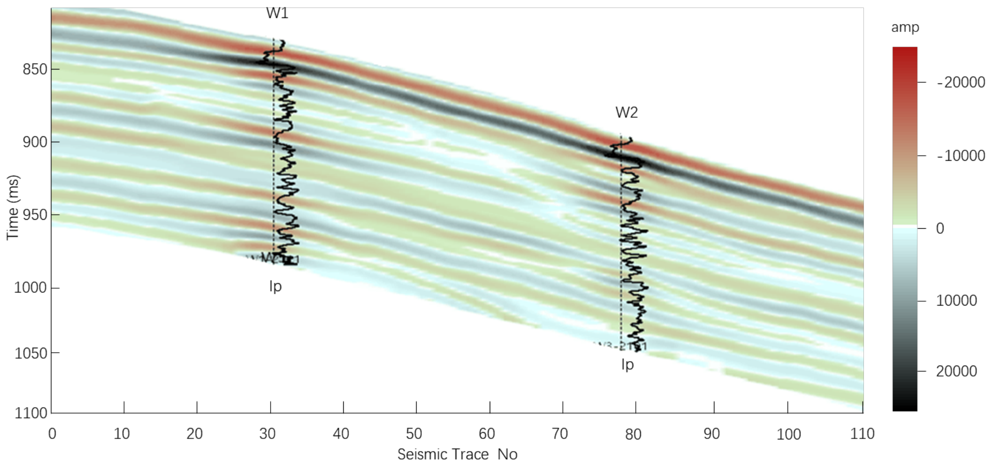
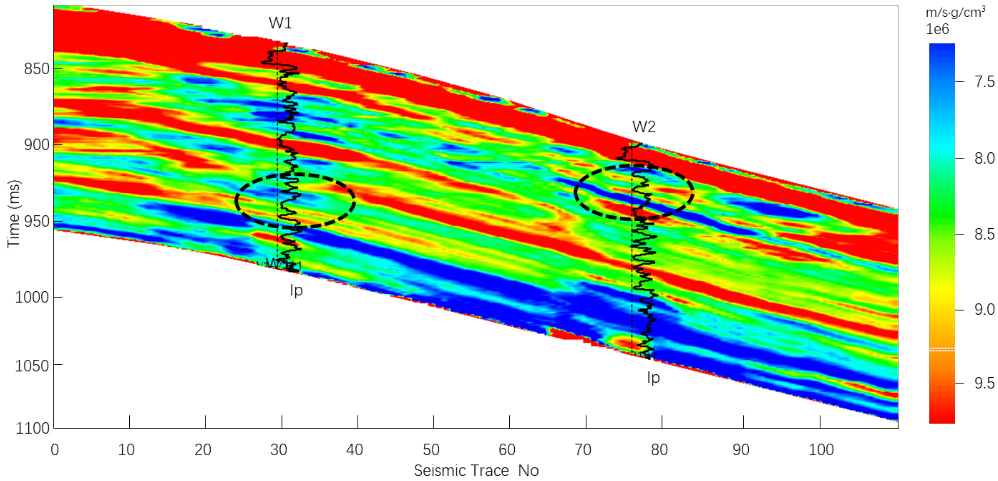


Fig. 8. Inversion results of the Overthrust model. (a) Inversion mapping model prediction inversion profile. (b) Inversion mapping model prediction inversion error. (c) TCN direct inversion profile (d) TCN direct inversion error. (e) TCN transfer learning inversion profile. (f) TCN transfer learning inversion error.



(a)



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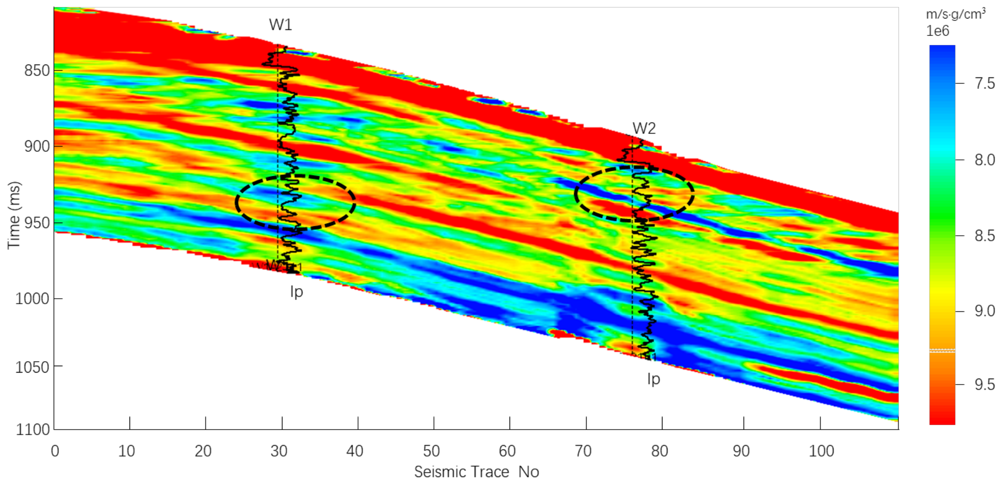

(c)

Fig. 9. Actual data. (a) Seismic profile. (b) TCN transfer learning inversion profile. (c) TCN direct inversion profile.

CONCLUSION

The impedance inversion method of TCN transfer learning is tested in two different models and data with similar seismic reflection characteristics in adjacent areas. The results show that: the transfer learning of seismic impedance inversion method to get better inversion results of the evaluation index, the Pearson coefficient, decision coefficient is higher, the convergence loss value is small, and the error which is compared with known information is small. Therefore, using a small amount of labeled data set can get a better generalization ability inversion mapping model, the evaluation is relatively reliable in terms of model data. Unfortunately, the evaluation reference information of the actual data inversion results is relatively weak, it can still be used as a potential inversion method for the target area with similar geological conditions in adjacent areas. However, the actual data are complicated, and there may not be a certain correlation between the data. Therefore, this method has certain application potential, and its universality needs to be further verified. More importantly, TCN transfer learning of the seismic impedance inversion focuses on the transfer learning of inversion mapping model. It is worth further studying how to avoid negative transfer learning when learning dataset features are updated iteratively to the model.

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