Acoustic Impedance Inversion Based on Transfer Learning Combined with Convolutional Neural Network and Residual Network

Introduction

Post-stack acoustic impedance inversion has definitive geophysical significance, which is a process of estimating acoustic impedance or velocity from seismic data, and acts an important role in lithofacies identification and hydrocarbon prediction. Traditional acoustic impedance inversion is based on convolutional model and requires low frequency model. When the definition of the initial model is not accurate, the impedance inversion is not credible. In addition, due to the filtering effect of seismic response, impedance inversion is band-limited.

Deep learning can establish the relationship between seismic data and acoustic impedance independent of the initial model, and has been rapidly developed. Various deep neural networks, such as convolutional neural network (CNN) (Das et al., 2018), recurrent neural network (RNN) (Alfarraj and AlRegib, 2019) and residual network (ResNet) (Wu et al., 2020) have been widely used in impedance inversion. However, deep learning is still facing many challenges. Firstly, due to the lack of available label data (well data) in field seismic inversion, the deep neural network with strong generalization ability cannot be trained. Secondly, in seismic exploration, different areas have different lithologies, so the network trained in one area cannot be applied to other areas. As an excellent strategy to apply knowledge learned in the source domain to the target data domain, transfer learning has been developed and successfully applied in various seismic exploration scenarios, such as first-break picking (Xie et al., 2019), automatic velocity analysis (Park and Sacchi, 2019), seismic impedance inversion (Wu et al., 2020), etc.

In this abstract, we designed a new network architecture named convolutional residual neural network (CRNN) for performing the nonlinear mapping from seismic data to impedance. Based on the convolutional model, we synthesize huge amounts of label data to train the network, which solves the problem of less label data (logging data) in field inversion. Then, we introduced transfer learning by using a small amount of logging data to finetune the pre-trained model for impedance inversion, which overcomes the problem that the pre-trained network is not fully applicable for impedance inversion in other areas. Layer transfer method is used to avoid overfitting in transfer learning. We utilize a Marmousi2 model and an Overthrust model to verify the effectiveness of transfer learning strategy.

Method

The architecture of CRNN for acoustic impedance inversion. The designed CRNN based on CNN and ResNet consists of three parts (shown in Figure 1) including a convolutional layer, four residual blocks and the regression module.

Residual blocks can reduce the optimization difficulty of deep network effectively by learning residuals. Different from the common ResNet network, CRNN uses convolutional layers with different kernel sizes to form residual blocks, which can extract the full frequency band of seismic

Figure 1 CRNN network architecture.
data at multiple scales. The regression module is composed of a convolutional layer and a full connection layer, which can map the features extracted from the previous module to the impedance parameters. Batch Normalization (BN) is used to accelerate the convergence and improve the generalization ability of the network. The rectified linear unit (ReLU) function is selected as the activation function to increase the nonlinearity of the network.

**Seismic data set preparation.** In deep learning algorithm, it requires a lot of ‘input’ and ‘label’ (desired output) data for training. Since there is little logging data as label data in the field inversion, a set of seismic data is generated randomly for network pre-training. The velocity range is between 1500m/s and 5500m/s to satisfy the requirements of the actual formation velocity model. This velocity model has 100 layers, and the thickness of each layer is random. We assume that the density is constant. The reflection coefficient (Figure 2) of each trace from the designed velocity model has different characteristics. The reflection coefficients are calculated by

\[
\begin{align*}
    r_i &= \frac{AI(t_{i-1}) - AI(t_i)}{AI(t_{i-1}) + AI(t_i)} \\
    \text{where } AI(t_i) \text{ is acoustic impedance. } r_i \text{ is the reflection coefficient of the interface.}
\end{align*}
\]

![Figure 2 (a) and (b) The reflection coefficients with different characteristics from the random velocity model.](image)

The convolutional model is adopted to generate a lot of seismic records with 30Hz zero-phase Ricker wavelet and reflection coefficient series, as follows

\[
    s(t) = \sum_{i=1}^{n} r(t_i) w(t - t_i) = r(t) \ast w(t)
\]

where \( s(t) \), \( r(t) \) and \( w(t) \) are a recorded seismic trace, the reflectivity series and source wavelet and in time domain.

**Transfer Learning (Layer Transfer).** The specific process of acoustic impedance inversion in this abstract is shown in Figure 3. Seismic records generated from random velocity are used as input and impedance is used as output for pre-trained network. The nonlinear mapping between seismic data and acoustic impedance can be simulated by data-driven method, which can be expressed as

\[
    F^{\Theta_1}_G(s) \approx AI
\]

Mean Absolute Error (MAE) can better reflect the error between the predicted impedance and the true impedance. The mapping between synthetic seismic data and acoustic impedance is learned during pre-training by minimizing the following loss function

\[
    Loss^{\Theta_1} = \frac{1}{N_G} \sum_{r=1}^{N_G} |AI - F^{\Theta_1}_G(s)|
\]

where \( \Theta_1 \) is the nonlinear mapping parameter of the pre-trained CRNN. \( N_G \) is the number of training data sets.

There are some differences between the data synthesized by convolutional model and the field data, so the network trained by model data is not effective in direct inversion of target domain impedance. As a machine learning technology, transfer learning can use the knowledge obtained from neural network in pre-training to complete another related task, which solves the above problems. In the target domain impedance inversion, we use the method of layer transfer to freeze all the layers before the regression module, and use the labeled target data to finetune the parameters of the regression module. Only a small number of parameters need to be finetune, which avoids the overfitting problem and speeds up the computation of learning process of the network. When finetuning the target domain inversion
network, the loss function is as follows

\[
\text{Loss}_{\theta_2} = \frac{1}{N_S} \sum_{i=1}^{N_S} |AI - F_{\theta_2}(s)|
\]

(5)

where \(\Theta_2\) is the nonlinear mapping parameter of CRNN for inversing in the target domain. \(N_S\) is the number of logging data in the target domain.

Figure 3 Transfer learning process. The network trained by large amounts of model data are applied for impedance inversion in target domain by transfer learning, and then the network is finetuned with a small amount of logging data to obtain the impedance inversion network in the target region. Freeze the feature extraction module and residual block module of the network architecture, and finetune the Regression module.

Examples

We choose two different geological models, Marmousi2 and Overthrust, as examples to conduct the numerical test to illustrate the inversion effectiveness of this method. Eight traces were extracted from the two geological bodies as logging data for finetuning network. Because there are few logging data, we set the batch size to 2 and the learning rate to \(1 \times 10^{-4}\). By means of transfer learning, the CRNN learns the reactivity characteristics of the new region, and the inversion results are accurate.

Marmousi2 model (Figure 4 (a)) has 2721 traces and 3495 sample points. Extracting eight traces (trace number 300, 600, 1000, 1300, 1700, 1900, 2300, 2600) from the Marmousi2 data as logging data.

Figure 4 (a) True impedance profile of Marmousi2. (b) The impedance profile predicted by the finetuned CRNN. Impedance traces from Marmousi2 model with trace number (c) 60, (d) 500, (e) 1200 and (f) 2000. Red curve represents true impedance. Blue curve represents impedance predicted by the pre-trained CRNN. Green curve represents impedance predicted by the finetuned CRNN.

Overthrust model (Figure 5 (a)) has 801 traces and 3700 sample points. Extracting eight traces (trace number 100, 180, 260, 320, 400, 480, 660, 780) from the Overthrust data as logging data.
Figure 5 (a) True impedance profile of Overthrust. (b) The impedance profile predicted by the finetuned CRNN. Impedance traces from Overthrust model with trace number (c) 20, (d) 110, (e) 200 and (f) 600. Red curve represents true impedance. Blue curve represents impedance predicted by the pre-trained CRNN. Green curve represents impedance predicted by the finetuned CRNN.

Figure 4 and Figure 5 show true impedance and estimated impedance. It can be seen from Figure 4 (c) and Figure 5 (c) that when the pre-trained network is directly used for impedance prediction in the other two regions, the prediction result is not accurate. After extracting 8 traces from the two models as logging data to finetune the network, it can well predict the low frequency trend of impedance, and has strong adaptability in complex areas. Because the network training is based on one dimension, there is no definite lateral space constraint, so there is jitter in two-dimensional profile (Figure 4 (b)) and Figure 5 (b)), which is a normal phenomenon in inversion based on one-dimensional network.

Conclusions

In this abstract, a method combining deep learning and transfer learning is used to inverse acoustic impedance. Independent of the initial model, the nonlinear relationship between seismic data and acoustic impedance can be established by CRNN. The network architecture trained by simulated data is finetuned with little logging data. Transfer learning not only overcomes the problem of less label data in field inversion, but also solves the approximation problem of convolutional model. We used two typical models with different geological characteristics to prove the effectiveness of the inversion method. This provides a new method for seismic inversion in field area.

Acknowledgements

This research is supported by the National Key R&D Program of China (NO. 2019YFC0312003) and the Strategic Cooperation Technology Projects of CNPC and CUPB (ZLZX2020-03).

References