Fracture-cavity carbonate reservoir identification based on adaptive seismic inversion

Introduction

Impedance is an essential property to identify ultra-deep fracture-cavity carbonate reservoirs. Numerous seismic impedance inversion methods are used to estimate impedance from seismic data. However, Complicated fault-karst system and low dominant frequency of real seismic data always impose a lot of limitations on the ultra-deep carbonate reservoir identification using conventional seismic inversion methods. Deep learning has progressed dramatically over the past few years. Many achievements have been made in the application of image recognition, natural language processing, autonomous driving, and other fields. The technology has been introduced to solve the problems of conventional inversion methods. Das et al. (2018) proposed a seismic impedance inversion method using 1D convolutional neural networks (CNNs). The method can generate training datasets under rock-physics modelling constraints. Alfrarraj and AlRegib (2019) used convolutional and recurrent neural networks (RNNs) to implement acoustic impedance inversion based on a semi-supervised framework. Biswas et al. (2019) proposed pre-stack and post-stack inversion methods to predict elastic parameters based on a physics-guided CNN. Mustafa et al. (2020) proposed a joint learning scheme to estimate acoustic impedance by simultaneously training two neural networks using different datasets. Dixit et al. (2021) estimated acoustic impedance inversion using a semi-supervised CNN with a genetic-evolutionary adaptive moment optimizer. Under the conditions of limited labels and quality of real seismic data, there are still many challenges for the practical application of the inversion method based on deep learning.

In this paper, we proposed an adaptive seismic inversion method to identify ultra-deep fracture-cavity carbonate reservoirs. The inversion model is based on a semi-supervised framework, which combines deep 1D CNN architecture and wave-propagation physics of classical seismic impedance inversion. We defined the adaptive objective function to be optimized. Seismic data and low-frequency impedance data are used to generate the inputs of the CNN-based model. The model can be trained without any real impedance labels, which can remove the limitation of insufficient labels. The inversion model can achieve better stronger learning ability and generalization, which is more suitable for impedance estimation and complicated reservoir identification. We demonstrated the effectiveness in the application of the proposed method on synthetic and real seismic data.

Method

Convolution operation of CNNs is similar to the forward waveform modelling that seismic traces can be obtained through reflectivity series convolved with a seismic wavelet. In this research, we modified a deep 1D CNN architecture for seismic impedance inversion. Figure 1 shows our CNN architecture based on a semi-supervised learning framework. The input layer can bring seismic data and low-frequency impedance data into the network. Hidden layers contain eight convolution layers to extract impedance features from seismic data. There are 32 convolution kernels in each of the first four layers, and 16 kernels in each of the last four layers. Kernel size is generally same as the length of seismic wavelet. Each convolutional layer is followed by additional batch normalization and rectified linear unit (ReLU) activation sequentially. The output layer is a convolution layer with 1 kernel to output prediction. We choose all convolution strides to 1 and remove pooling operations so that the dimension of predicted results can match that of the inputs. In addition, the CNN architecture for inversion is flexible. The number of convolution layers can be appropriately increased or reduced according to the quality and size of seismic data.

During training, seismic data and low-frequency impedance data are fed into the CNN-based inversion model. Features related to impedance can be extracted automatically from the seismic data through the convolutional operations layer by layer in the forward propagation step. We add up the low-frequency data and prediction of the output layer as the predicted impedance. The predicted impedance is further used to calculate reflectivity and convolve a wavelet to generate corresponding synthetic seismic data. The error between the real seismic data and synthetic seismic data is calculated as seismic waveform loss. It can be written as:

$$\mathcal{L}_s = \frac{1}{n}\sum_{i=1}^{n}(S_i - S_i')^2 \tag{1}$$

Where S_i is the real seismic data. S_i' is synthetic seismic data. $\mathcal{L}_s$ is the seismic waveform loss term. Low-frequency impedance data are used to constrain the network and improve its performance. We use low-frequency constraint loss to calculate the error between the low-frequency impedance data and predicted impedance. It can be written as:

$$\mathcal{L}_f = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2 \tag{2}$$

Where y_i is the input of low-frequency data, y_i' is the predicted impedance. $\mathcal{L}_f$ is the low-frequency constraint loss term. We defined the final objective function to be optimized. The function consists of a seismic waveform loss term and a low-frequency constraint loss term. It can be written as:

$$\mathcal{L} = \lambda\mathcal{L}_s + (1-\lambda)\mathcal{L}_f \tag{3}$$

Where $\mathcal{L}$ denotes the objective function to be optimized. λ and 1-λ are the weight factors of the two loss terms respectively. However, the weight factors have a great influence on the performance of the CNN-baed model. In general, the weight factor λ of seismic waveform loss should be larger than the low-frequency constraint loss. Although we can choose the fixed values for the weights during training, it may not be suitable for all seismic traces. In this research, we add two fully-connected layers to connect the last convolution layer. They are used to adaptively learn the weight factors for each seismic trace during training. There are 16 units in the first fully-connected layer, and 1 unit in the second layer. the weight factor λ can be written as:

$$\lambda = k + (1-k)q \tag{4}$$

Where k is a fixed value in the range of 0.5-1 before training. q is a dynamic scale factor in the range of 0-1 from the last fully-connected layer. λ will be changed dynamically during training, which can improve the performance of the CNN-based model. Gradients of the objective function are calculated and optimized to update the weights and biases of the CNN architecture in the back-propagation step.

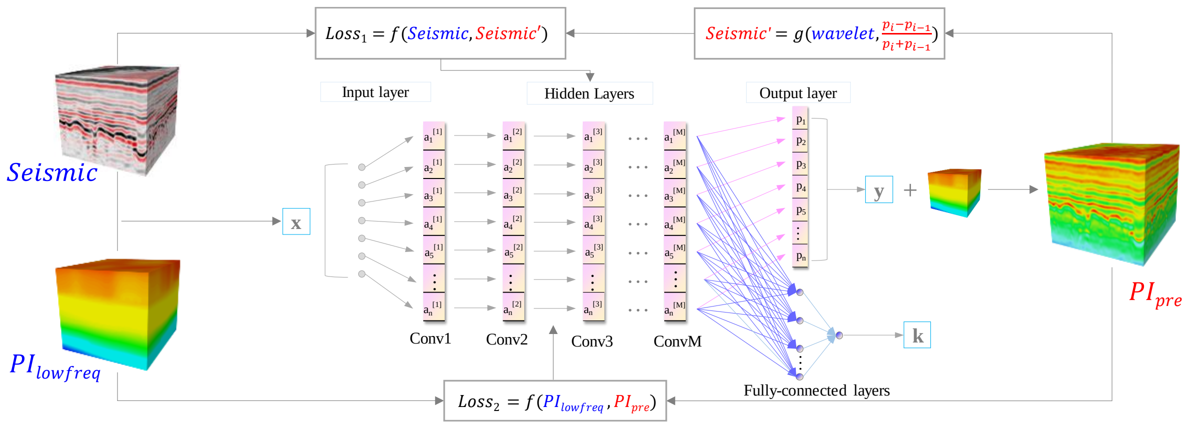

Figure 1 *The proposed CNN-based architecture and workflow for seismic impedance inversion.*

Application

The performance of our proposed method is first evaluated on a synthetic seismic data. We collected an small impedance volume from a seismic survey in the Tarim Basin, China. Ultra-deep fractured-cavity carbonate reservoirs are our exploration targets. The impedance volume was estimated by using a conventional deterministic inversion method to identify the reservoirs. It contains 5710 traces with 10 inline and 571 crossline. We used the impedance data to calculate reflectivity, and further convolve a Ricker wavelet to generate a synthetic seismic data. The dominant frequency of the wavelet is 30Hz. The impedance data was low-pass filtered to obtain the low-frequency impedance data within 8Hz. We predefined the k to 0.7 to calculate the weight factors of loss terms before training. 10% of the synthetic data and low-frequency data were selected randomly as training datasets to train the network. Adam (Kingma and Ba, 2014) was used to optimize the network during training. The CNN inversion model was trained 300 epochs with a batch size of 32 and a learning rate of 0.001. Finally, we used the trained model to perform impedance inversion on all synthetic data. Figure 2b and Figure 2d show the comparison of the true impedance and predicted results on the Inline 1. It is obvious that the impedance predicted by our method is consistent with the true impedance. The fractured-cavity carbonate reservoirs with different scales can be characterized accurately using predicted impedance.

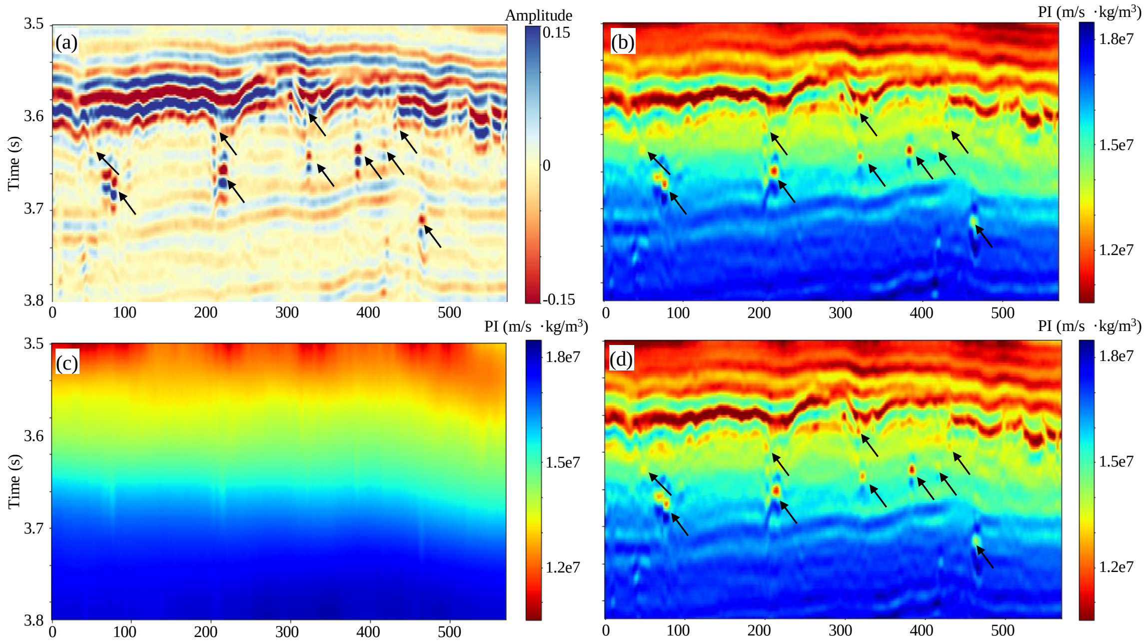

Figure 2 *The Application on synthetic data. (a) Synthetic seismic data. (b) True impedance data. (c) The low-frequency data from the true impedance data using a low-pass filter. (d) The impedance predicted using our proposed method.*

Figure 3 is the comparison on the CDP 320 of Inline 1. The comparison shows that the predicted impedance is in good agreement with the true impedance. The predicted impedance can accurately identify the fractured-cavity carbonate reservoirs, which indicates the good performance of the CNN-based inversion method.

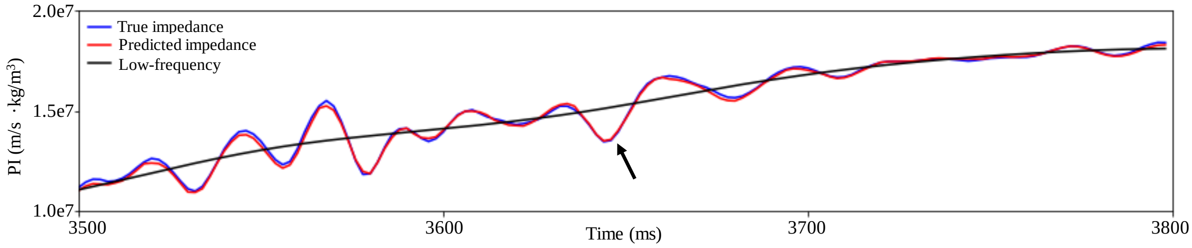

Figure 3 *Comparison between the true impedance and predicted impedance by the proposed method on the CDP 320 of Inline 1.*

We also demonstrated the proposed method on real seismic volume with the target of ultra-deep fractured-cavity carbonate reservoirs in the Tarim Basin. Low-frequency data was generated from impedance logs of wells and seismic horizons. The scale of the real seismic volume is very large, so we only randomly selected 1% of the data to generate training datasets. To compare with our proposed method, we also employed a commonly used conventional deterministic inversion method to perform impedance inversion. Figure 4(a) and 4(b) show comparison of inversion results. Both methods can be used to characterize the large-scale fractured-cavity carbonate reservoirs, but the black arrows and circles indicate that the CNN-based method can provide more impedance information to identify the small-scale reservoirs. The comparison proves that our proposed method achieved better performance.

Conclusions

In this work, we proposed an adaptive inversion method to estimate seismic impedance and identify the ultra-deep fractured-cavity carbonate reservoirs in a semi-supervised framework. The proposed method provides a practical solution to train a CNN-based inversion model without measured impedance labels, which can remove the limitations of insufficient labels. We defined the inversion objective function that consists of the seismic waveform loss term and the low-frequency constraint loss term with corresponding weight factors. The CNN-based model can adaptively learn the dynamic weight factors in the objective function during training, which can improve the performance of the network. The application on synthetic and real seismic data indicates that our proposed method can predicted more accurate impedance to identify fracture-cavity carbonate reservoirs.

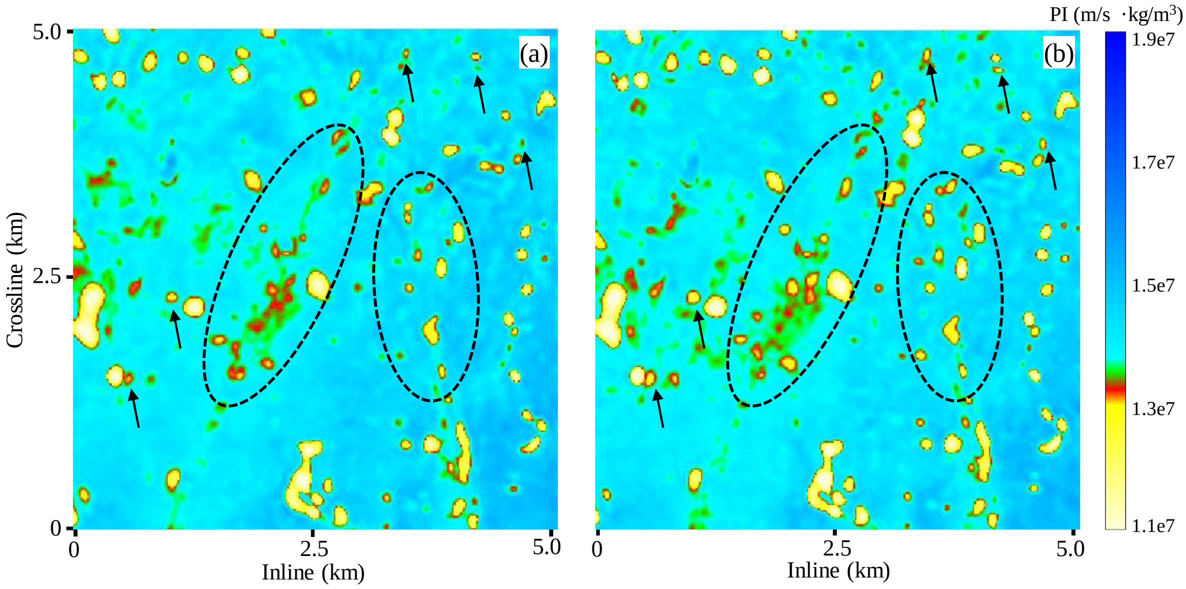

Figure 4 *Application and comparison on a 3D real data. (a) The impedance estimated by a conventional inversion method. (b) The impedance estimated by our proposed method*

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