A DEEP LEARNING VELOCITY MODELING METHOD BASED ON A NOVEL ATTENTION MECHANISM NETWORKS

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ABSTRACT

Interpretation of seismic surveys is severely constrained until subsurface velocity information is extracted by seismic survey interpreters. Velocity modeling is an important aspect of seismicity, and the extraction of accurate velocities of subsurface media is an important parameter for obtaining high-precision imaging. Conventional velocity information can be obtained by layer inversion and full waveform inversion (FWI), but the conventional methods are computationally intensive, affected by the quality of acquired data, and expensive. In recent years, the technology of deep learning has been widely used in the field of seismic exploration. In this paper, deep learning convolutional neural network is introduced, which can build the velocity information of this data directly from seismic data. Attention Unet network distinguishes itself from the traditional network, which can realize the target area by attention according to the observation of demand. Different from the traditional inversion method, the deep learning method is based on the training of big data. In the training phase, the network maps key information from the seismic simulation data into a velocity model. The reconstruction of the data can be completed based on the training. In a large number of experimental data validation results show that the method has achieved better results. The output results can obtain accurate velocity information of underground medium.

KEY WORDS: Attention mechanism; Deep learning; Unet; FWI; Velocity modeling

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INTRODUCTION

Accurate velocity information is necessary to obtain accurate imaging results for seismic interpretation. Velocity modeling techniques have been continuously developed and improved, and many techniques such as offset velocity analysis (Al-Yahya and Kamal, 1989), tomography (Chiao and Kuo, 2001), and full-waveform inversion (Yang et al., 2013) can build relatively accurate velocity models. These methods usually use either frequency-domain data or time-domain data and test the velocity model by minimizing the difference between observed and simulated data. There are some limitations in the use of traditional methods due to the high computational cost and the interference of inversion results by multiple factors.

Nowadays, many optimization methods are continuously proposed. For example, the proposed full-waveform inversion methods in Laplace domain and Laplace-Fourier domain can not only improve the accuracy of the inversion, but also be applied to the field data (Shin and Cha, 2008, 2009). The FWI technique has been developed continuously, and a lot of achievements have been made in the inversion strategy, algorithm optimization, construction of initial model and computational efficiency. The comparison of four optimization methods in full waveform inversion for elastic waves was studied (Liu et al., 2022). The 3D three-bit elastic waveform full waveform inversion based on region decomposition was realized in the 3D processing that fits the field data (Qin et al., 2023). The above methods are all improvement strategies in different directions for the FWI method, but the FWI method still faces serious challenges in terms of memory consumption, computational cost, and actual production(Gui et al., 2017).

In the mid-1980s, nonlinear intelligence techniques were applied. Neural networks were first utilized in 1994 for inversion in seismic exploration (Roth and Tarantola, 1994). After continuous research and development, neural networks were utilized in predicting fault information from seismic traces, and the prediction results were tested to be not only accurate but also greatly save manpower (Wu and Chang., 2014). In order to obtain high-precision inversion results, deep learning methods are combined with FWI to improve the quality of salt dune inversion. By learning the relationship between observed data and media model features through Convolutional Neural Network (CNN), the trained network can act in the FWI method (Lewis and Vigh, 2017). Through this idea of transformation, inversion is viewed as a transformation between different domains, which is realized between the seismic data domain and the velocity model domain based on a deep convolutional generative adversarial network approach (Mosser et al., 2018). In the same line of thought and approach, velocity models can be reconstructed using all seismic trace data and global seismic profiles (Li et al., 2019). The field data is no longer a standard depth-domain velocity model, and using the analyzed velocity spectra as a dataset, a method to introduce deep learning into seismic velocity modeling based on a conventional convolutional neural network was implemented (Araya_polo et al., 2018). Network training is also a relatively large computational project, in order to reduce the training time, a Monte Carlo-based method was investigated to reduce the training dataset and train the network more efficiently by selecting part of the seismic dataset (Jia et al., 2018). In order to solve the prediction of salt mound model has been a difficult point in seismic exploration. In order to improve the accuracy of salt body prediction, a full convolutional neural network was utilized to detect salt bodies on raw shot records, and the comparison was found to be faster and more efficient than the traditional method (Wang et al., 2018). The accuracy of petrographic prediction for single wells can also be improved using the BP neural network approach (Zhou et al., 2020). In the actual Dutch Groningen gas field, the deep learning approach accelerated the modeling of the Dutch Groningen gas field (Haibin et al., 2022).

Deep learning techniques have been continuously applied to overcome many difficulties in the field of seismic exploration. For velocity modeling methods, from the first use of deep learning techniques to improve the accuracy of FWI inversion, it is now possible to predict velocity information directly in the original seismic record. In 2019, a velocity modeling technique based on real-time data-driven technology was applied using an anti-network approach for improving velocity model accuracy (Zhang et al., 2019). On this basis, direct velocity modeling using full-waveform seismic data was proposed, such as a direct velocity modeling method using full-waveform seismic data based on FCN (Yang et al., 2019); and a CNN-based method to estimate the background velocity model directly from the original seismic data without pre-processing or pre-training (K. Øye and E. Dahl, 2019). This shows that deep learning neural networks can extract meaningful velocity information from real gun sets, demonstrating potential applications in velocity modeling. To further improve the accuracy, inversion with constraints can be achieved based on fully connected neural networks, and the deep learning method can directly eliminate or pick up bad points, completely eliminating manual checking and modification and improving the modeling efficiency (Zhao, 2019). The initial prediction of the network is further come to be refined by iteratively optimizing the network parameters, and the accuracy of the inversion is further improved using this constrained method (Liu et al., 2023). With known initial velocities and field seismic data, mapping between the time-shifted data domain and target data variations can be achieved using the simplest fully convolutional neural network (Yuan et al., 2020). Most of the deep learning velocity modeling method studies since then have been based on initial velocities and field seismic data, which are also more consistent with the actual physical meaning. In order to solve practical and complex near-surface problems, deep learning is used to predict the near-surface velocity modeling method, which expands another application idea of deep learning (Wang et al., 2022). In order to further simulate to get accurate seismic data, using different grids, different differential orders and physical simulation methods, a data-driven deep learning component was utilized to achieve high-precision inversion of seismic data (Sun et al., 2021).

In summary, this paper proposes a deep learning velocity model construction method based on seismic simulation data driven by the field seismic data is known. The accuracy of the inversion results is improved by optimizing the original Attention-U-Net network model. The workflow of this paper is shown below:

Step 1: Using Improved Attention U-Net, establish the mapping relationship between the seismic simulation record and the corresponding velocity model;

Step 2: Construct two datasets and make predictions, comparing the FWI method with the traditional UNet method;

Step 3: Input the validation set to obtain the predicted velocity model.

THEORY

Conventional full-waveform inversion(FWI) methods

The core idea of FWI is to utilize the optimal matching of observed and simulated data for subsurface media modeling, but full waveform inversion still has many difficulties, such as instability and strong nonlinearity of the inversion problem.

The theory of full waveform inversion is based on:

$$E(m) = \frac{1}{2}\left\| d_{obs} - d_{cal} \right\|_2 \tag{1}$$

where *obs* represents field recorded data, *cal* represents simulated recorded data, and *m* represents the velocity model.

In the process of algorithm implementation, it is necessary to derive the target generalization. The model parameter m of Eq. (1) is derived:

$$\begin{aligned} \frac{\partial E(m)}{\partial m_l} &= -\frac{1}{2}\sum_{i=1}^{n}\left[\frac{\partial d_{cal_i}}{\partial m_l}\left(d_{obs_i} - d_{cal_i}\right)^* + \left(d_{obs_i} - d_{cal_i}\right)\frac{\partial d_{cal_i}}{\partial m_l}\right] \\ &= -\sum_{i=1}^{n}\mathrm{R}\left[\left(\frac{\partial d_{cal_i}}{\partial m_l}\right)^T \left(d_{obs_i} - d_{cal_i}\right)^*\right] \end{aligned} \tag{2}$$

where *R* denotes taking the real part. This equation expresses the relationship between the first-order partial derivatives $\frac{\partial E(m)}{\partial m_l}$ of the target generalized function and the real part of the transpose of the wavefield residual Äd .

The gradient operator of the target generalized function is the gradient of the target generalized function with respect to the model parameters, i.e., the vector consisting of the partial derivatives of each model parameter in the target generalized function. According to Eq. (2), we can then obtain the expression of the gradient operator of Eq. (1) as:

$$\nabla E = \frac{\partial E}{\partial m} = -\Re\left[\left(\frac{\partial d_{cal}}{\partial m}\right)^{\mathrm{T}}\left(d_{obs} - d_{cal}\right)^{*}\right] = -\Re\left[\mathbf{J}^{\mathrm{T}}\Delta d^{*}\right] \quad (3)$$

Assume that there is an optimization step α which must make the initial objective generalization $\nabla E(\alpha)$ zero. A second-order Taylor expansion of the error generalized function takes the same form as the second-order Taylor expansion of the velocity. Thus when $\nabla E(\alpha) = 0$, the optimization step can be expressed as:

$$\alpha = \frac{\| g(m) \|^2}{\tau} \quad (4)$$

$$\tau = 2\frac{\mathrm{E}\left(m_p\right) - \mathrm{E}(m) + \alpha_0 \| \mathrm{g}(m) \|^2}{\alpha_0^{\ 2}} \quad (5)$$

Where τ represents the result of taking the second order partial derivative of the residual vector with respect to the velocity.

To summarize, the flow of the full waveform inversion is shown as follows;

Step 1: Select a suitable initial model, set the observation system, set the error termination conditions, the maximum number of iterations, etc;

Step 2: The initial model performs forward simulation, calculates the residual difference between the simulated record and the observed data, and calculates the objective function value as well as the gradient;

Step 3: Calculate the gradient and calculate the step size;

Step 4: update the velocity field;

Step 5: determine whether the error termination condition and the maximum number of iterations are reached, when completed, output the velocity model, when not, repeat steps 2 to 4;

Step 6: output the final velocity model.

U-Net network architecture with improved attention mechanism

The U-Net network, a classical neural network first applied to medical image segmentation, is an Encoder-Decoder structure, where the Encoder, or encoder, is used to extract features from the input image, and the Decoder decoder reduces the features to an image.

The model proposed in this paper is shown in Fig. (1) below, which introduces jump connection and *Fusion* attention on the basis of U-Net network. In which the encoder compresses the spatial dimension of the input seismic data by multilayer convolution and downsampling to obtain its high latitude information and feature potential representation. Then the decoder uses inverse convolution for feature reduction and velocity modeling. The novel U-Net network, *Fusiond* Attention-based Velocity Modeling Network (Fusion Attention-U-Net), proposed in this paper, introduces the novel *Fusion* Attention mechanism. This network addresses the problem of seismic velocity modeling and achieves efficient data conversion from seismic simulation records to velocity models through end-to-end learning of neural networks.

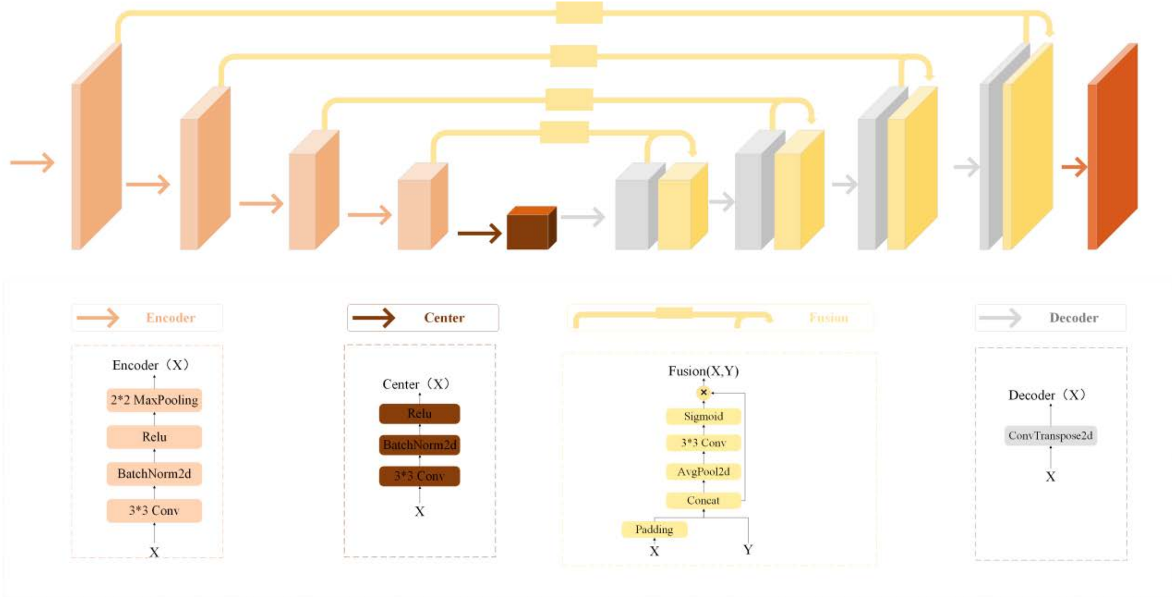

Fig. 1 Optimized network structure model

The network as a whole can be represented as:

$$Vmodel = FAN(shot(nx,nt,ns),w) \tag{6}$$

where *shot* denotes the original seismic shot record, *nx* denotes the length of each excitation point geophone, *nt* denotes the reception time of the acquisition record, *w* denotes the weight parameter of the deep learning network, and *Vmodel* denotes the velocity model.

The encoder uses convolution and downsampling layers to achieve feature extraction as follows:

$$Encoder(shot) = MP\left(ReLu - BN\left[Conv(shot)\right]\right) \tag{7}$$

Where *MP* denotes maximum pooling and the pooling parameter is set to 2 to achieve downsampling. *Conv* convolution kernel size is set to 3. *padding* parameter is 2. step size is 2 to achieve feature extraction in the same dimension. *ReLu* activation function and *BN* normalization are used to prevent the network from the gradient explosion problem. The middle *Center* layer is used as a central layer to connect the encoder and decoder, and a layer of convolution is used to achieve feature transfer as shown below:

$$Center(X) = ReLu - BN\left[Conv(X)\right] \tag{8}$$

The decoder's feature decoding is implemented using inverse convolution, also known as transposed convolution, which is the inverse process of convolution that allows for semantically inclusive decoding:

$$Decoder(x) = ConvTrans(x) \tag{9}$$

In this paper, we propose the novel *Fusion* Attention Module. The attention mechanism is derived from the different levels of human attention to specific regions, and is commonly used in deep learning to emphasize key regions of features. In this paper, the *Fusion* attention mechanism is used to enhance the network's attention to features at the edges of velocity mutations, as well as focused regions, which can be represented as:

$$Z = Fusion(x, y) \tag{10}$$

where x denotes the feature vector of the encoder part, y denotes the vector of the corresponding dimension of the decoder, and z denotes the feature vector of the output.

In this paper, the *Fusion* module is applied in four different dimensions and the application to the network can be represented as:

$$Output = \sum_{1}^{n} Fusion(X_i, Y_i) \tag{11}$$

For extracting x from the encoder, which is the pre-vector of the network, in order to improve the generalization performance of the network as well as to dimensionally align it with y, it is first padded with *padding*, i.e.

$$x1 = pad(x) \tag{12}$$

Then y is concatenated with $x1$, and the two are merged to perform feature fusion through subsequent steps:

$$y1 = Concat(x1, y) \tag{13}$$

Given the layer design of the overall network, i.e., four layers each for the encoder and decoder, in order to improve the advanced semantic information extraction of the network in the shallow layer, the information *fusion* of the front and back features is strengthened by using average pooling in the fusion module,and then $y2$ is obtained by summarizing the vectorial features of the encoder and decoder from the detail side after a 3*3 convolutional layer:

$$y2 = AP\left[Conv(y1)\right] \tag{14}$$

where AP denotes average pooling AvgPool.

The *Fusion* attention mechanism is accomplished by applying different weights to the *Feature map* to emphasize the features, and using the *sigmod* function on the $y2$ vector, the attentional weights are projected into the interval

[0,1] to obtain the *attentional* coefficients:

$$att = \sigma(y2) \tag{15}$$

where σ denotes *sigmod*, is used as a projection function, and then the *att* information is pixel-producted with the original fusion vectors to obtain a feature map containing the attention weights, which is fed to the deconvolution in the decoder for velocity model reconstruction.

$$y_{output} = att * y1 \tag{16}$$

The whole process can be represented as:

$$y_{output} = a(P[Conv(concat(Pad(x), y))]) \tag{17}$$

With the *Fusion* attention module, the time domain data x and depth domain data y are realized with feature fusion and key information enhancement to ensure the efficient implementation of the network for seismic velocity modeling.

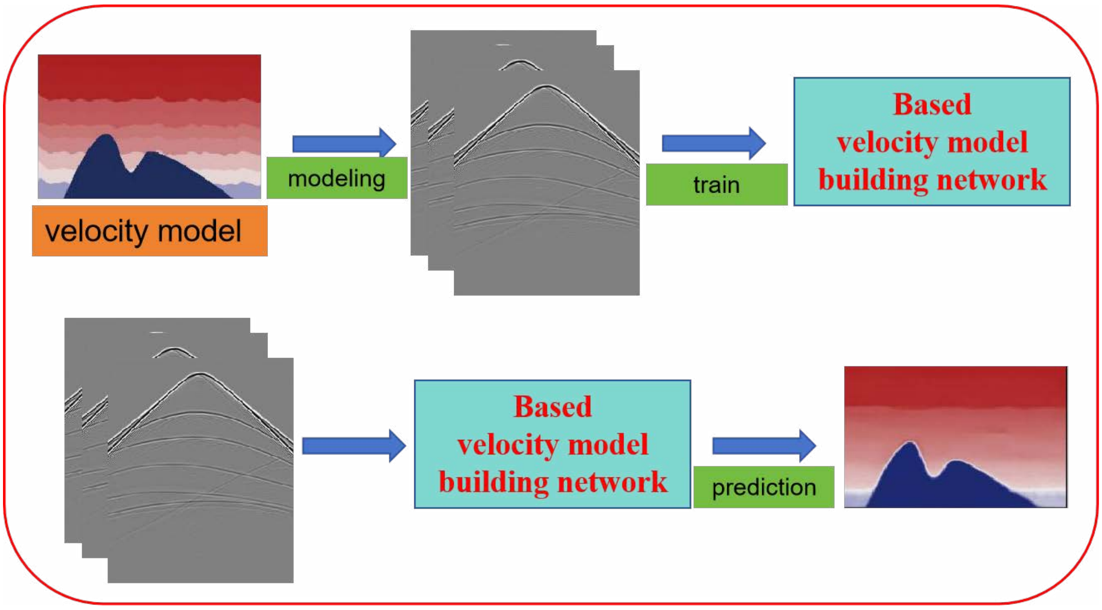

Fig. 2 Schematic flow of data training as well as prediction

CONSTRUCTION AND VALIDATION OF THE DATASET

Training dataset preparation

To validate the accuracy of the methods in this paper, the data sets are the simulated data set and the SEG salt dune data set. The simulated data training set has 1600 velocity models without duplicates. The SEG salt dune model has 130 trained data models. Some of the data for the simulated dataset is shown in Figure 3 and some of the data for the SEG data is shown in Figure 4. The model size of the dataset is 301*201, the grid spacing is 8 m, the maximum velocity is 4500 m/s, and the minimum velocity is 1500 m/s. In order to quickly and accurately get the simulated gun records corresponding to each velocity model, the corresponding shot records are obtained by using the optimized nine-point finite difference solving the fluctuation equation in the frequency domain. For each velocity model, 29 excitations were made at the surface of the seismic source, and all 301 geophones were received at the surface, with a geophone interval of 8 m. The sampling interval was 1 ms, the sampling time was 2 s, and the main frequency was 30 Hz. Fig. 5 shows the simulated gun records for some of the corresponding velocity models. Figure 5 shows that the simulated data have a high signal-to-noise ratio and no frequency dispersion.

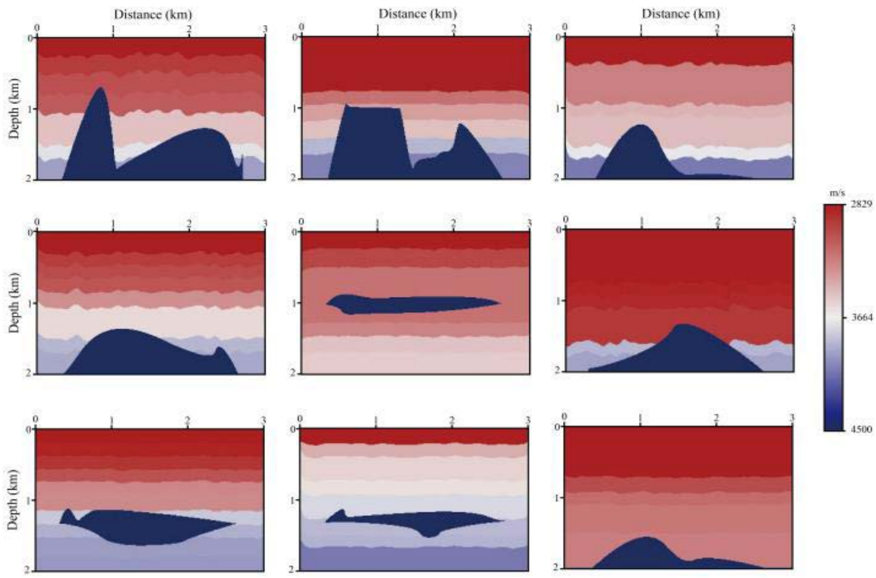

Fig. 3 Simulated data training set

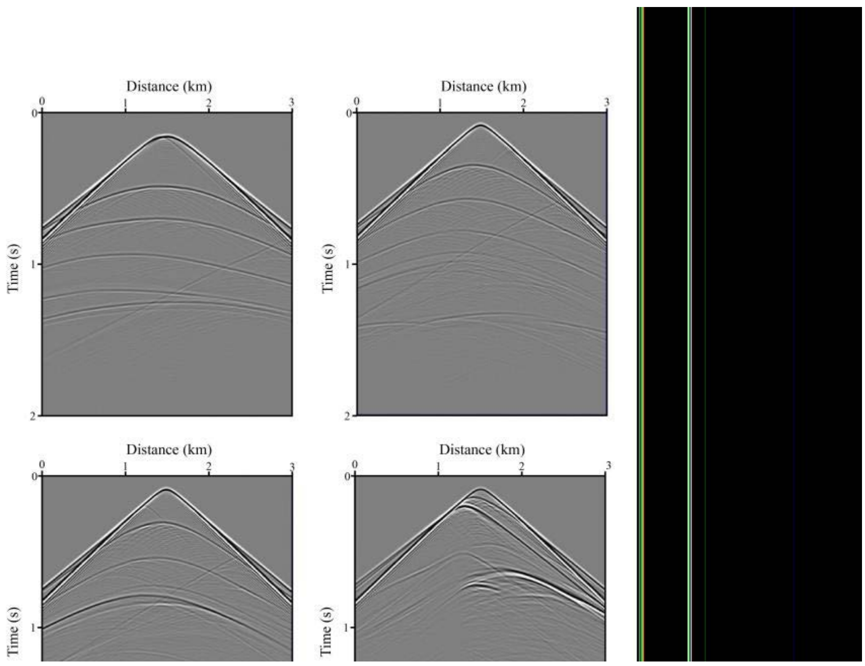

Fig. 4 SEG data training set

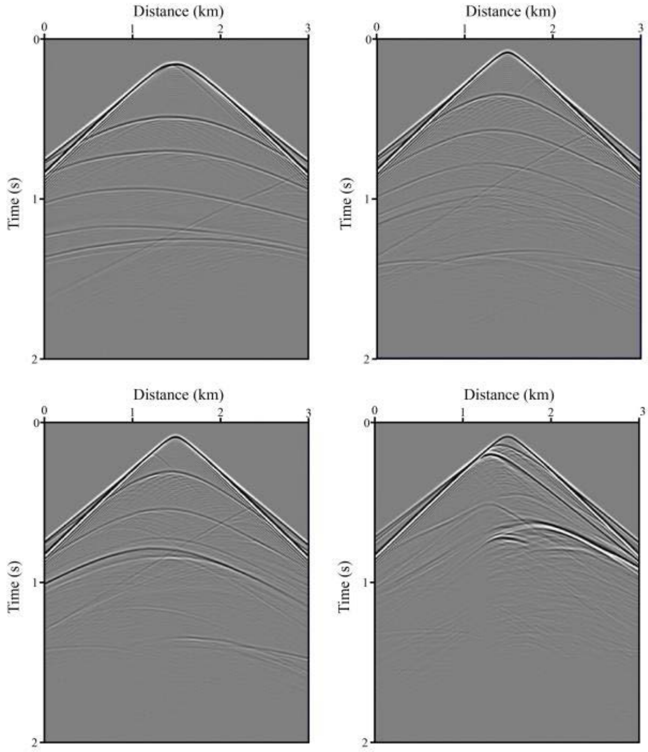

Fig. 5 Schematic of a single gun for some of the training data

Test Data Set

In this paper, the validation results are compared with the traditional U-Net network method and FWI method to prove the effectiveness, accuracy and efficiency of the method. In order to make the network training optimal, the simulated data test set with 100 different speed models and SEG salt dune model with 10 tested speed model data sets are prepared. Figure 6 shows a part of the test set of simulated data and a part of SEG is data.

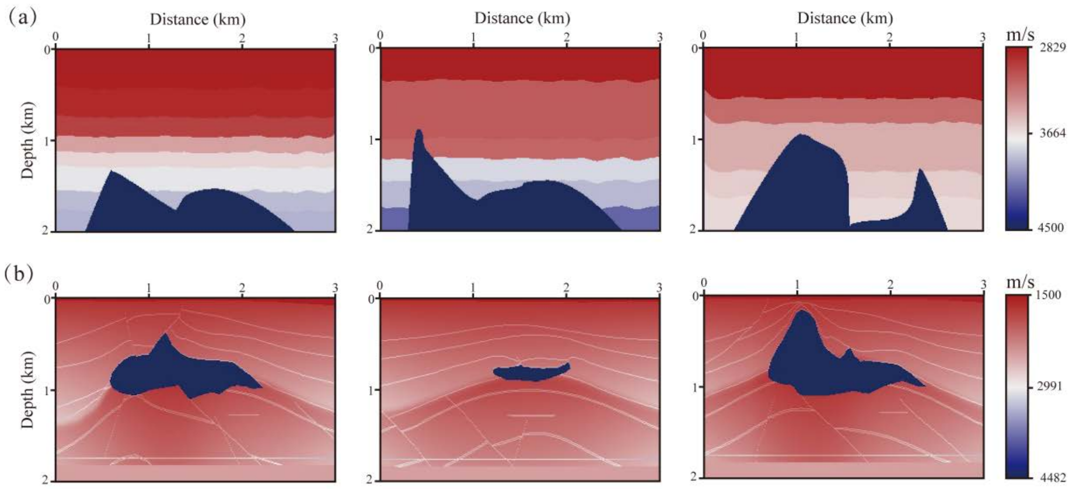

Fig. 6 Simulated data part of the test set

Verification results

The initial validation model, FWI inversion results and the new network structure inversion results in this paper are shown in Fig. 7. Figure 8 shows the analysis of the extracted 80th and 200th lane speeds, and the comparison gets that the deep learning predicted speed model is closer to the real speed. Figure 9 shows the inversion results of the other speed two velocity model, the same 80th and 200th channel speeds are extracted for curve analysis, and the comparison shows that the speed predicted by the deep learning method is more accurate. As obtained by inverting the four models, the inversion accuracy of the deep learning method is better than that of the traditional FWI method. Especially at the deep level, the inversion results of deep learning methods outperform those of conventional methods.

It is also found that the FWI method iteratively calculates the velocity model for 25 iterations takes 11.5 h to get the inversion result, but the deep learning method takes only 2.5 min to get the desired inversion result, which largely saves the computation time compared to the full waveform inversion method deep learning prediction method.

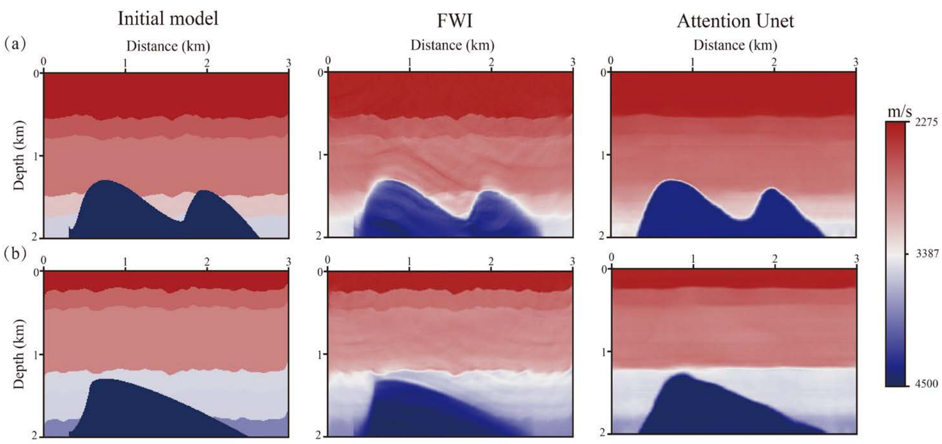

Fig. 7 Demonstration of the results predicted by the simulated dataset

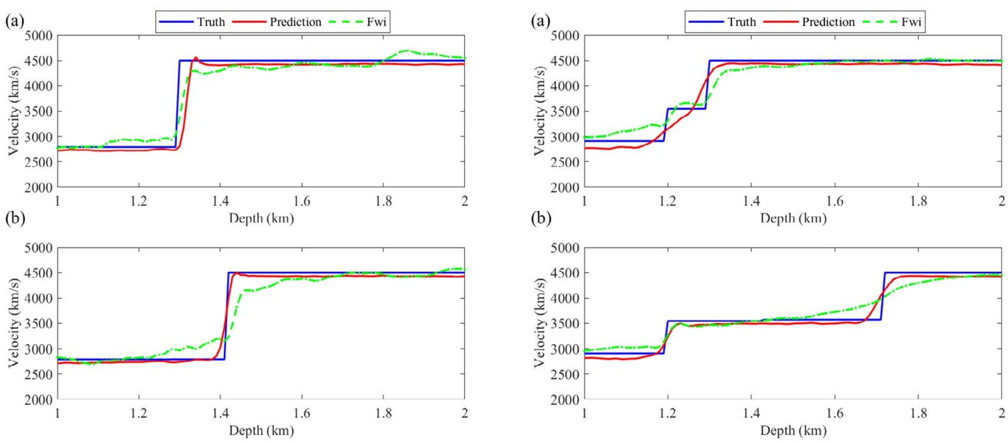

Fig. 8 On the left, the 80th and 200th pass velocity analysis of the prediction results in Fig. 7(a); on the right, the 80th and 200th pass velocity analysis of the prediction results in Fig. 7(b)

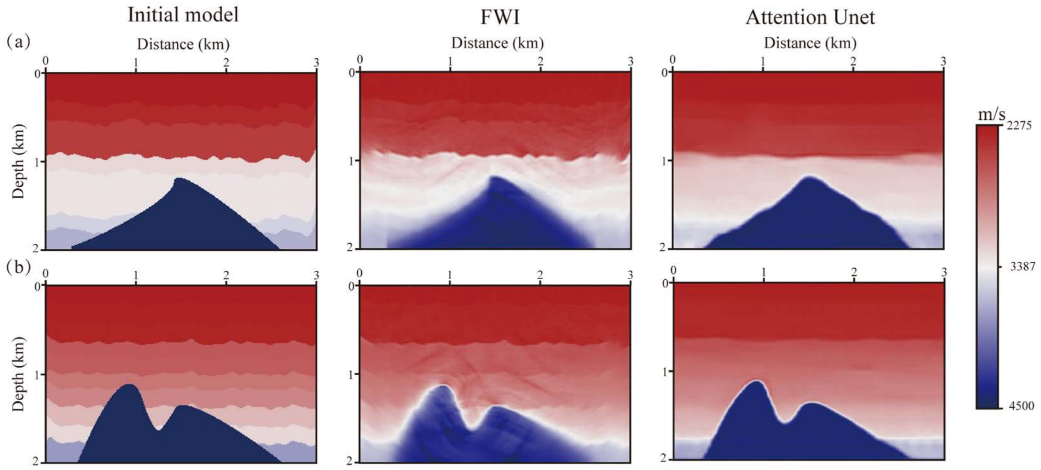

Fig. 9 Presentation of the results predicted by the simulated dataset

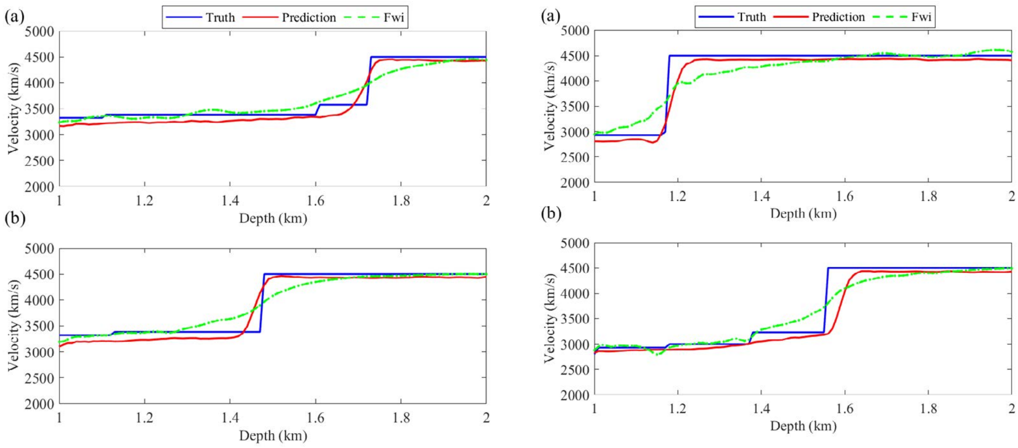

Fig. 10 On the left, the 80th and 200th pass velocity analysis of the prediction results in Fig. 9(a); on the right, the 80th and 200th pass velocity analysis of the prediction results in Fig. 9(b)

CONCLUSION

In this paper, an improved attention mechanism network is proposed to establish a relationship between simulated records and velocity model by training the seismic numerical simulation records and velocity model, which can realize the inversion work of seismic data, and the improved network can further enhance the since relationship between seismic records and velocity model. Through the salt mound model test analysis obtained, the method proposed in this paper can not only save the calculation time, but also can accurately replace the calculation function of the FWI, and the accuracy of the model prediction has been improved by the improvement of the attention mechanism network. In order to the future work, should study how to solve the field data in the field, the fiela data is a work containing a huge amount of computation, need to further optimize the work in this paper to solve the problem of computation. And it is necessary to design the deep learning network architecture that matches with the field data, which is very necessary.

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