Research on Seismic Exploration Velocity Modeling Based on Deep Learning

Dianguang Gai [1], Tingmei Tang [1, *], Hui Li [2]

[1] Seismological Bureau of Shandong Province, Jinan 250014, China

[2] Shandong Institute of Commerce &Technology, Jinan 250103, China

* Corresponding Author Email: 770847540@qq.com

Abstract. As the core parameter of seismic exploration, seismic wave propagation velocity runs through the seismic exploration process. The construction of reasonable and accurate velocity models is an important basis for exploration technologies such as high-precision seismic offset imaging, data processing and interpretation. The current velocity modeling strategy is limited by the target geological body, which has a long calculation period, high calculation cost, and is seriously affected by human subjective factors, and its adaptability to complex geological formations is poor. Based on this, this paper studies the accurate speed modeling method of universities. Firstly, the principle of earthquake detection is analyzed, and then the speed modeling based on improved fully convolutional neural network is studied. A velocity modeling fully convolutional neural network (VNB-FCN) is constructed to directly extract geological features from seismic data and establish a high-precision velocity model. Compared with the traditional velocity modeling method, the VMB-FCN model effectively avoids the problem of excessive dependence of neural networks on standard seismic datasets, and improves the accuracy and efficiency of seismic exploration velocity modeling.

Keywords: modeling speed; deep learning; neural networks; Seismic exploration.

1. Introduction

Seismic exploration is a very effective geophysical exploration method in oil and gas exploration, which uses artificial methods to excite elastic waves into the ground. The elastic wave is refracted and reflected underground through the interface of the rock formation, and the highly sensitive receiver is used to receive the elastic wave back to the ground at the surface, and the collected seismic exploration signal is analyzed to understand the underground geological structure and find oil and gas reservoir resources. Since the nineties of last century, with the emergence of large-area three-dimensional seismic exploration technology and high-density seismic exploration technology, the amount of seismic data has also increased rapidly. The development of seismic exploration technology has also brought new challenges to the interpretation of seismic data [1]. The manual interpretation of seismic data faces the problems of large workload and low efficiency, and has a certain degree of human subjectivity, and the accuracy of the results depends on the experience and knowledge of the interpreters themselves. With the continuous development of deep learning technology, it has been widely used in natural language processing, image recognition and other fields and has achieved remarkable results [2]. In order to improve the drift imaging quality of seismic data, it is necessary to establish a sufficiently accurate velocity model. Traditional velocity modeling methods can no longer meet the actual needs of seismic offset imaging quality. This paper aims to build a reasonable and accurate velocity model, and focuses on high-precision velocity modeling methods under the framework of deep learning by introducing deep learning methods in the field of artificial intelligence, so as to provide new ideas for improving the imaging accuracy and speed modeling efficiency of seismic exploration.

2. Principles of seismic exploration

Seismic exploration is often used to find oil and gas resources, conduct geological or crustal studies. Due to the different materials and densities between different underground formations, when there are waves propagating in the formation, encountering these different media will produce different propagation speeds and attenuation, or different reflection and refraction phenomena. This results in different times when the ground detector receives the wave and the characteristics of the wave [3]. By analyzing and processing these data, we obtain the propagation law of waveforms underground, so as to analyze whether there are precious oil and gas resources underground or analyze the geological structure. Therefore, seismic exploration is one of the very important methods in geophysical exploration, and its process generally includes three parts: data collection, data processing and data interpretation.

2.1 Collection of data

Data collection in seismic exploration uses artificial sources (e.g., cannons) to cause ground shaking, generating elastic waves to propagate through the formation. Due to the presence of substances of different media in the formation, the elastic wave will encounter these substances with different reflection and refraction phenomena, and the propagation speed will also be different, and then the detector placed along the measurement line is used to receive these waveforms, and finally the data acquisition process can be completed by amplifier and recorder processing [4]. The collected seismic data has a great relationship with the source and geophone location, geological strata characteristics, etc., among which the location of the source can be selected as the middle firing arrangement, or the endpoint firing arrangement. The survey line can be a conventional straight line or multiple lines designed to obtain three-dimensional data within a certain area of the ground. In order to improve the quality of the collected data, it is necessary to ensure the quiet of the collection environment as much as possible and avoid the occurrence of human noise as much as possible, so as to be more conducive to the subsequent analysis of the collected data.

2.2 Processing of data

The data processing process is to process the original seismic exploration data collected in the process of collecting the above-mentioned data. Its main purpose is to suppress the noise that interferes with the effective reflection of information, improve the signal-to-noise ratio and resolution of seismic exploration data, and pave the way for subsequent data interpretation [5]. When collecting data, due to the surrounding environment, human reasons and the machine itself, the collected data contains a large amount of noise, and the effective reflection information is not easy to identify, and its characteristics cannot be well analyzed. Suppressing noise to obtain seismic data with a high signal-to-noise ratio is very important for seismic exploration. At present, there are more and more methods of data processing, but the generalization ability needs to be further improved.

3. Construction of earthquake velocity model based on deep learning

3.1 Deep learning seismic velocity modeling process

In seismic exploration, the propagation of seismic waves in the underground is usually affected by the physical and chemical properties of underground rock layers and reflected to the surface, and exploration researchers draw seismic profile images according to the information received by the geophones arranged on the surface [6]. The different areas in the profile represent a variety of different geological formations, so seismic profile images can be thought of as natural textured images that reflect subsurface geology. We combine image segmentation methods in deep learning to improve the pickup efficiency and accuracy of boundary structure and stratum information in seismic profile images, so as to achieve velocity modeling or improve the accuracy of the initial velocity model [7]. The process of directly building a velocity model using deep learning methods is shown in Fig. 1.

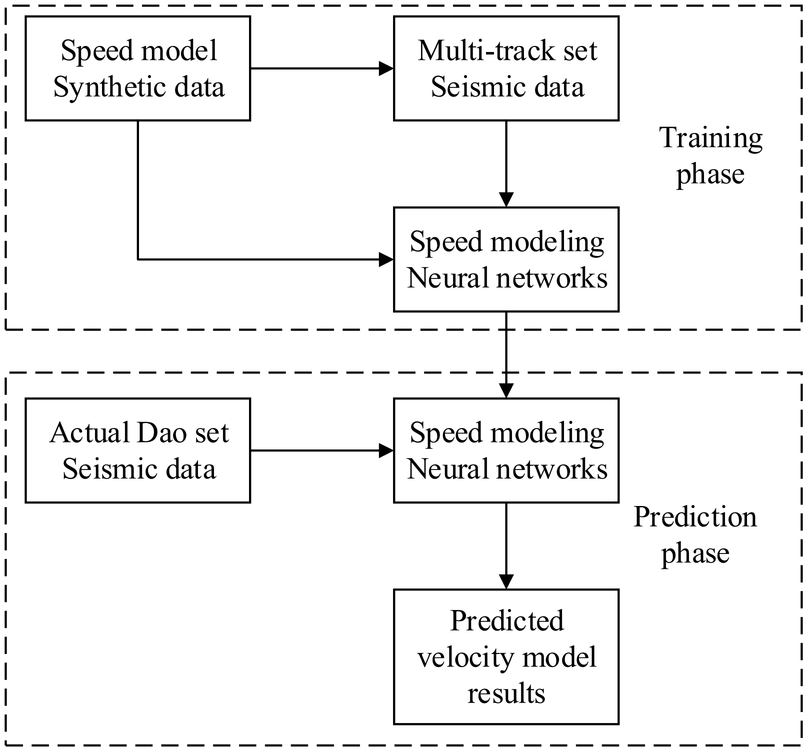


Fig. 1 Deep learning methods directly build velocity model processes

As can be seen from Figure 1, unlike traditional speed modeling methods, deep learning direct speed modeling methods rely heavily on the training of neural networks and the quality of the dataset. In the network training stage, it takes a lot of time, the training is completed, the speed modeling can be completed in a few seconds, this process does not require human participation, and does not require the initial speed model and model repeated reconstruction. Among them, for the design problem of neural network architecture, this paper can obtain by training the neural network (GA-CNN) algorithm by genetic algorithm, so as to avoid relying on repeated tuning tests of neural networks.

3.2 Convolutional neural network structure diagram

Convolutional neural networks are one of the most classic algorithms in deep learning, which is inspired by the visual neural structure of living things. The convolutional neural network structure is very simple, as shown in Fig. 2. Through the convolutional layer, activation function, pooling layer and fully connected layer, three parts are composed of input, feature extraction and output. For input, this part is used to receive data, which can be a one-dimensional time series or a two- or three-dimensional array, which is one of the reasons why convolutional neural networks are widely used. For feature extraction, this part is the main component of convolutional neural network, which is generally stacked repeatedly through three common structures: convolutional layer, activation function, and pooling layer [8]. For output, this section is used to output the predictions of the model, using fully connected layers as the output structure in the diagram, and convolutional layers can also be used.

The workflow of convolutional neural network is divided into forward propagation and reverse propagation: forward propagation is that the input data is processed by convolution, activation and pooling of the feature extraction part, transmitted layer by layer, and finally output; Backpropagation is to obtain the error between the network output and the label by calculating the loss function, and the error is backpropagated back to the network by using the chain law to optimize the network parameters. In this paper, earthquake velocity modeling is based on convolutional neural networks.

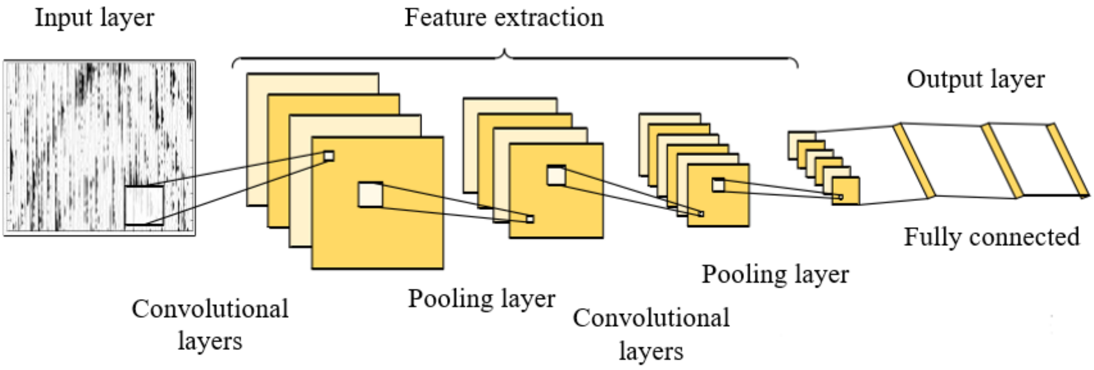


Fig. 2 Convolutional neural network structure diagram

3.3 Fully convolutional neural network seismic velocity modeling

Due to the obvious advantages of CNN feature learning and expression ability, it is a priority method in the field of image semantic segmentation. This paper makes full use of the feature extraction capability in Best-CNN network architecture to reduce the difficulty of manually reconstructing and debugging the network. To build the velocity modeling neural network architecture (VMB-FCN), Best-CNN was refined into a neural network architecture capable of automatic seismic velocity modeling from raw seismic data, combined with FCN and U-Net network architecture concepts, as shown in Fig. 3. The VMB-FCN neural network architecture includes two parts: one is the contraction path for capturing geological features (left half), and the network architecture of Best-CNN is adopted to improve the feature extraction ability of the network; The other part is to use deconvolution to upsample the feature map (right half) to achieve pixel-level intensive prediction. The numbers below the network layer indicate the number of output feature channels, and the numbers on the left indicate the feature map size [9]. The symmetric form of VMB-FCN is similar to the encoder-decoder structure of U-Net, and VMB-FCN uses hop connection to directly stitch the feature map in the encoder, effectively fusing deep detail information and shallow semantic information. VMB-FCN uses dense connections in the encoder part, fuses dense feature maps, makes full use of context information and spatial location information in geological features through hop joins, and utilizes convolutional layers with step 2 and convolutional kernel size 3 and convolutional layers with step 1 and convolution kernel size 1 to reduce the amount of parameters while improving the generalization ability of the model [10].

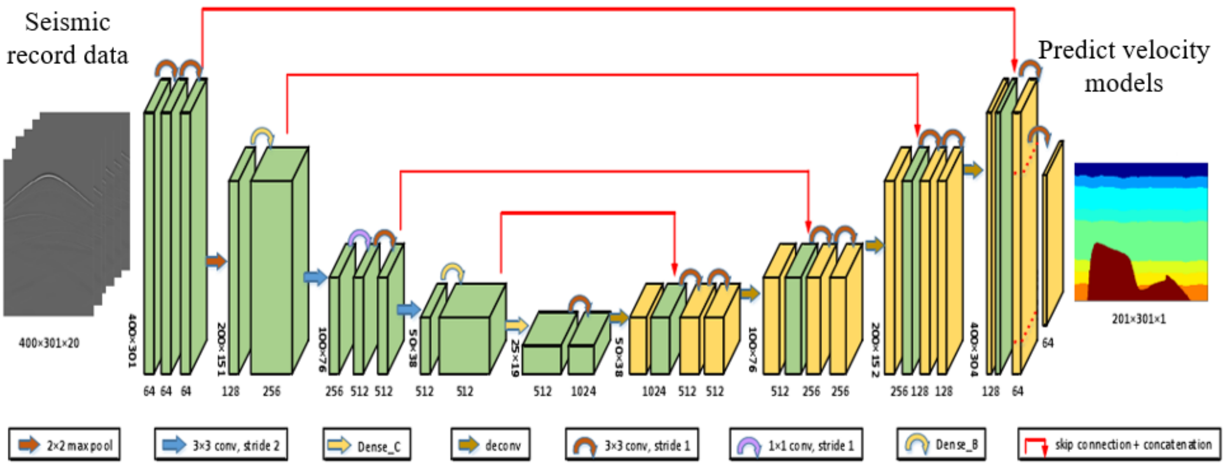


Fig. 3 Neural network architecture for earthquake velocity modeling

In order to build a fully convolutional neural network that can realize earthquake velocity modeling, the input and output of the network model are improved accordingly. Traditional FCN mainly reads the RGB color channel of the image as input image information, but the processing of seismic data requires multiple gun point lane set information as input to the network. These channel sets are generated from different source locations of the same velocity model, so the number of input channels to the network is the same as the number of sources for each velocity model. Simultaneous input of seismic data from multiple sources into the network can improve data redundancy. On the other hand, for an ordinary FCN, the input and output are in the same image domain, and this paper realizes the construction of the velocity model by converting the seismic data information from the data domain to the model domain. To this end, in the final output section of VMB-FCN, this paper truncates the feature image size obtained by 3×3 convolution to the same size as the velocity model, and sets the output layer channel to 1.

The basic idea of VMB-FCN neural network for earthquake velocity modeling is to establish a mapping relationship between input (seismic multi-track set data) and output (velocity model), which can be expressed as follows.

$$\tilde{V} = Net(s;\omega) \tag{1}$$

Where $Net(\cdot)$ represents the VMB-FCN network architecture constructed in this paper and its nonlinear expression, s represents the seismic multi-track set data, ω represents the set of learning parameters of the neural network, including weights and thresholds, and $\tilde{V}$ represents the speed model predicted by the network.

4. Experimental results and analysis

In order to verify the effectiveness of the VMB-FCN neural network model constructed in this paper for speed modeling, the proposed method is experimented on a Linux server with GTX 2080Ti GPU and Ubuntu 22.10.

During training, the loss function degradation curve of the VMB-FCN neural network is shown in Fig. 4. It can be seen that at the beginning of the curve, the network training is relatively slow, and after iterating 10 epochs, the network extracts more seismic data features, the training speed is accelerated, and the loss curve decreases smoothly during the training process.

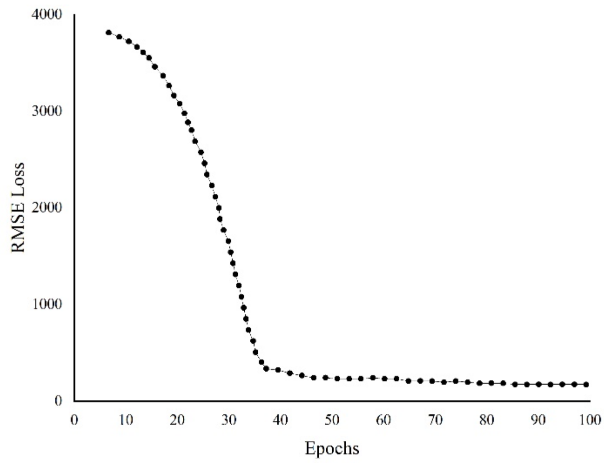
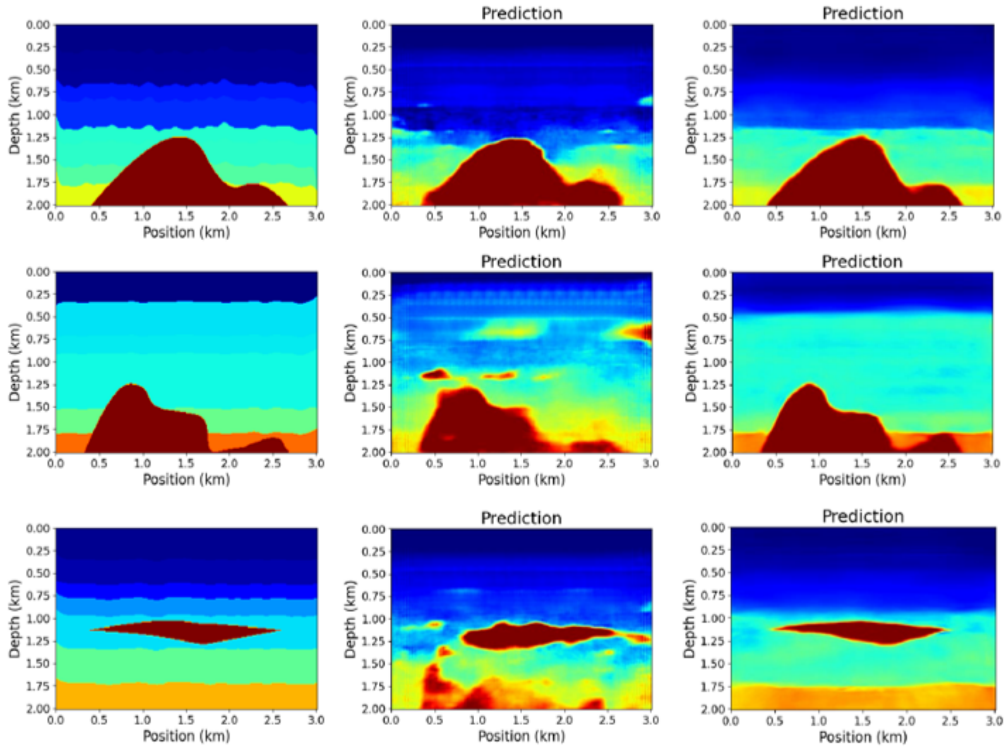


Fig. 4 Loss function descent plot for VMB-FCN neural networks

Finally, the trained VMB-FCN neural network is tested using the test data, and in order to visually illustrate the performance of the speed modeling of the proposed method, the traditional U-Net neural network model is also used for training as a comparative experiment of the results of the VMB-FCN method. Fig. 5 compares three of the prediction velocity models in the test data. It can be seen from

Fig. 5 that among the modeling results of the three test velocity models, there is a big gap between the velocity modeling results of the U-Net neural network and the real velocity model, and it is impossible to learn the geological features well, especially for the salt dome area with large deep velocity values, which is quite different from the contour of the real velocity model. The VMB-FCN velocity modeling network constructed in this paper has better results in the three results, the interface and strata information are clearer, and the shape of the salt dome in the velocity model has been accurately depicted, indicating that the VMB-FCN velocity modeling network can better learn geological features and prove the effectiveness of the method.



a) Realistic velocity model b) U-Net modeling results c) VMB-FCN modeling results

Fig. 5 Modeling results of VMB-FCN and U-Net on a simulated velocity model

5. Conclusion

With the continuous development of deep learning technology, the method of using neural networks for image segmentation of seismic data has also been widely used. Deep learning provides an accurate and effective way to efficiently model velocity using large amounts of seismic data. In this paper, a speed modeling method based on improved fully convolutional neural network is proposed. This method uses the neural network architecture search algorithm to search for the neural network architecture with the global optimal feature extraction ability on the agent task, and constructs a velocity modeling fully convolutional neural network, which improves the accuracy and efficiency of velocity modeling by directly entering seismic data to establish a velocity model. In the study of velocity modeling methods based on deep learning, due to the limitations of actual standard seismic datasets, there are still cases where the speed details are not accurate enough. At the same time, the processing of 3D seismic data is limited by the size of GPU memory, and the corresponding deep learning speed modeling scheme needs to be studied at a deeper level.

References

[1] Xie J., Cheng X. Q. (2023) A review of deep learning applications in seismic localization. Journal of Earthquake Engineering,2023(01):235-243.

[2] Zhang W. H., Yin L. (2023) Optimization algorithm for seismic detection of missed alarms based on CNN and BiLSTM. Intelligent Computers and Applications,13(02):169-173.

[3] Zhang Y., Zhou Z. F., Song L. W., et al. (2023) Low-frequency delayed topology of seismic data based on physically constrained U-Net network. Petroleum Geophysical Exploration, 58(01):31-45.

[4] Wei J. D. (2019) Seismic data characterization: velocity and acceleration. Petroleum Geophysical Exploration, 54(02):243-253+235.

[5] Wang X. W., Rao Y., Liu M. S., et al. (2020) Analysis of vibration characteristics of seismic exploration in the Yellow River Delta depression area. Blasting,37(03):40-46.

[6] Ren L. G., Zhang J. (2021) Analysis and application of conversion of acceleration signals into velocity signals in seismic exploration. Advances in Geophysics,36(01):380-385.

[7] Mou X. G., Zhou Q., Zhou X., et al. (2021) A research on an improved seismic interference algorithm with high frequency expansion. Journal of Instrumentation,42(04):59-66.

[8] Jiao Y., Wei J. S., Lian Y. G., et al. (2022) Development and application of delay correction technology for slot wave seismic exploration. Energy and Environmental Protection,44(03):127-131.

[9] An H. S. (2022) A multi-channel reflection time-depth conversion method for shallow seismic surveys. Journal of Geology,46(02):152-157.

[10] Cheng J. Y., Zhang X. X., Jiang B. Q., et al. (2023) From 1D to 4D: Technological progress and inspiration of seismic exploration in coalfield. Coalfield Geology and Exploration,51(01):247-258.