An Extraction Method for Discontinuity Surface and Velocity Anomaly from Seismic Profile Images based on Deep Learning

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Abstract: A novel method for extracting discontinuity surface and velocity anomaly from seismic profile is presented based on deep learning, which from the wide-angle reflection/refraction profile of deep seismic sounding, seismic tomography and wave equation migration method for receiver function imaging. This method could automatically obtain discontinuity velocity structure and velocity anomaly information for different seismic profiles. The classification results, which are verified by the obfuscation matrix algorithm, could express the crustal structure and velocity stratification better, and obtain the velocity anomaly information.

Keywords: Deep learning, Seismic profile, Discontinuity surface, velocity anomaly, Structure of seismic wave velocity

1. Introduction

Seismic profile is an image of geological structure distribution, which is extracted from original seismic data. According to different seismic attributes and methods, the final geological structure image is established by different seismic wave attributes. Due to the difficulty in obtaining original data and the complexity and variability of geological structures, there are differences for multi-source seismic profiles based on a single seismic attribute [1]. The processing of different attributes data is complicated and difficult to fuse based on multiple seismic attributes imaging. The classification of seismic profiles can provide support for the comparison and fusion of different seismic attribute images by geospatial analysis method, and the classification of seismic imaging profiles avoid tedious manual interpretation and classification based on deep learning method [2-4]. This method can process different seismic profile data and automatically obtain discontinuity velocity structure and velocity anomaly information in multi-source seismic profiles.

At present, the understanding of crust and mantle structure mainly depends on the velocity structure obtained by seismic waves. Seismic exploration methods for obtaining crustal and mantle structures mainly include wide-angle reflection/refraction profile of deep seismic sounding, seismic tomography and wave equation migration method for receiver function imaging [5-7]. The deep seismic sounding profile, which is sectioned from the P-wave velocity structure, is used to obtain the data of seismic wave phase characteristics with different attributes at various depths such as crust-upper mantle and lithosphere structures. Relying the natural seismic wave travel time data of fixed seismic network, the tomographic imaging method can invert P-wave or S-wave velocity structures from the crustal and lithospheric in two or three dimensions. Wave equation migration method obtains the crust and mantle structure for receiver function imaging by the travel time from dense passive seismic arrays, and the result is a S-wave velocity structure. However, the crust and mantle structures obtained by the above methods are imaged based on different seismic exploration methods, and there are differences in depth and morphology of the crust obtained by velocity imaging of different seismic waves. For the crustal structure and spatial distribution characteristics of boundary morphology of different structures further study, How to obtain the information of the intersections and velocity anomalies from different seismic profiles is helpful, and this experiment also provides a more reliable image of crustal structure for exploring the relationship between crustal structure and seismic activity.

Confounding matrix method is used to verify the classification results of crustal structure. This algorithm is a widely used image classification accuracy evaluation method based on deep learning in the world. Its core is a comparison matrix, which contains the number of pixels and the number of test categories [8-10]. The columns in the array represent the reference data and the rows represent the category data from the image data classification. Obfuscation matrix is a statistical algorithm, which needs to count the correct pixel number, the wrong pixel number and the total pixel number corresponding for different categories. Ultimately, image classification data based on deep learning can obtain different accuracy evaluation indexes through different algorithms.

2. Proposed Seismic Profile Image Classification Method based on Velocity Attributes

Seismic profiles are imaged based on velocity properties, and the results do not classify the formation

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and velocity anomalies. So profiles need to be classified through spatial analysis including cropping, focal statistics, reclassify, vectorization and turn surface grid. These functions could correct seismic profile boundaries, remove noise image, and generate the classification labels of stratum and velocity blocks. The crustal and upper mantle structure images obtained by the above method provide raw data and tag data for the method for automatically extracting seismic wave velocity structure discontinuity surface and velocity anomaly based on deep learning. Seismic section editing work is divided into discontinuity surface extraction and velocity anomaly extraction.

2.1. Data Processing

Firstly, the seismic profile data is cropped to remove the redundant boundary, and the image of the crust and mantle velocity structure containing the annotation is obtained. Seismic profiles are interpreted images of stratified crustal structure, and these profiles can be vectorized into discontinuity surface layers including sedimentary strata, upper crust, lower crust, Mohorovicic discontinuity and asthenosphere layer. Through the vector dataset of discontinuity surface, discontinuity surface label dataset which are raster image could be generated by classifying the layers. Next, using image processing and focus statistic methods remove the noise which is generated by seismic profile labeling, and obtaining the crust and mantle structure images. According to the regional geological interpretation data, the velocity structure composed of local layers and velocity anomalies is obtained from the seismic profile Images, which are reclassified and vectorized. This step can remove the broken surface and the unclear surface of classification, and obtain the label dataset of the classification of speed structure.

2.2. Construct Deep Semantic Segmentation Network

Semantic image segmentation is an image processing method that classifies every pixel on the image. Fig.3 shows the Construction of deep semantic segmentation network technology flow chart. Convolutional networks are often used for classification tasks, and where the output of an image is a single category label. The network is modified and extended accordingly to enable it to run with fewer training images and to make more precise segmentation operations. Figure 1 shows the overall structure of the network, which is mainly composed of contracting path and expanding path. The contracting path is used to obtain context information, and the expanding path is expanded for precise localization. The two paths are symmetrical to each other. The contracting path follows a typical convolutional network structure, which uses a modified linear unit activation function and a maximum pooling operation for downsampling. At each downsampling step, the number of feature channels is doubled. In the expanding path, Feature map requires running upsample and up-convolution to reduce the number of feature channels by half. Next, the feature map after corresponding clipping in the contraction path needs to be connected, and the corresponding activation function is selected to carry out two convolution operation. In the last layer of network, the convolution operation of 1*1 convolution kernel is used to map eigenvectors to the network output layer.

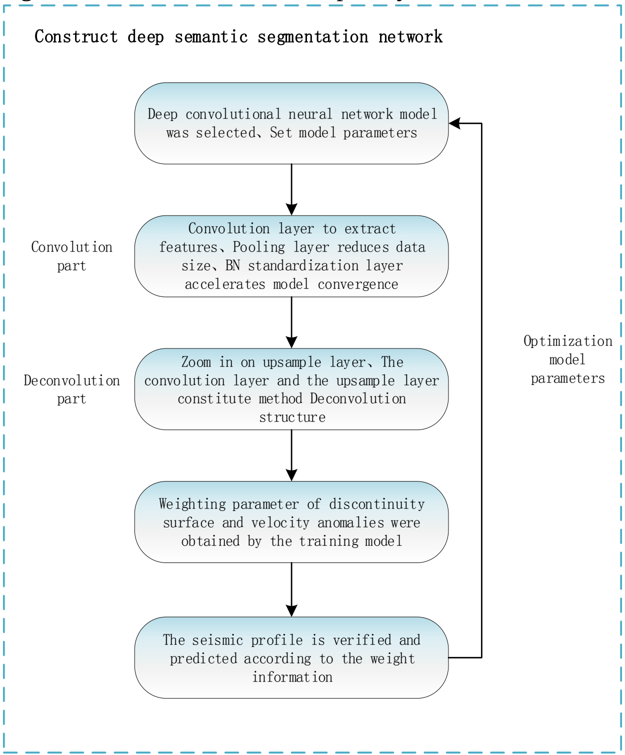

Figure 1. Construction of deep semantic segmentation network technology flow chart

3. Deep Learning Image Classification Result and Verification Method

According to the above methods, the image standard dataset is acquired through coordinate correction, cropping and other pretreatments, the training set and test set are made by data enhancement and cutting to scale, and the validation dataset is made by priori knowledge and artificial interpretation. The parameters of convolutional layer, pooling layer and upsample layer were determined and the training of deep semantic segmentation network was established to obtain the fusion image feature weight file. To predict the test set and verify the credibility of the weight file, adjust the cutting size and network parameters to obtain the best feature weight file of fusion image and standard dataset. Finally, the automatic batch extraction, which obtains the boundary feature information of main discontinuity surface and velocity anomaly is realized in seismic profile.

Figure2 shows the training results of three-dimensional P-wave velocity 3D model and S-wave velocity 3D model of the north China craton (NCC). In stratification, the crustal structure is divided into four layers by three interfaces. The first layer is the interface between sedimentary cover and crystalline crust，and the last two layers are the upper and lower crust interface and Moho

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surface. Comparing the prediction and sample of P-wave velocity structure longitude 114 section, the prediction results show the hierarchical structure of the crust. In the stratification of velocity structure, velocity values are divided into nine categories to better show the distribution of velocity structure and velocity anomalies in the crust. Comparing the prediction and sample of S-wave velocity structure longitude 108 section, the prediction. The prediction results retain all of the information in the velocity structure sample.

Figure 2(a) Crustal structure classification label of the NCC P-wave velocity 3D model

Figure 2(b) Crustal structure classification prediction of the NCC P-wave velocity 3D model

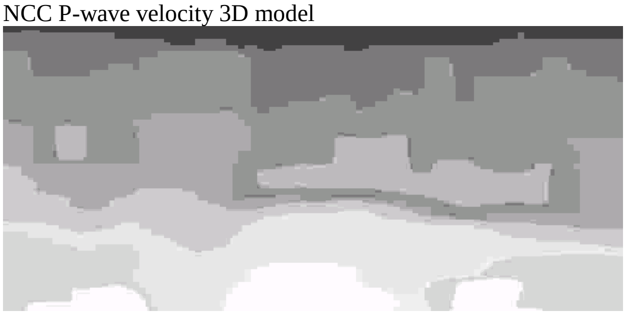

Figure 2(c) Speed structure classification label of the NCC S-wave velocity 3D model

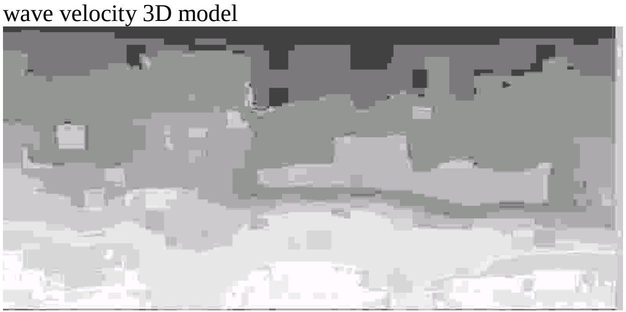

Figure 2(d) Speed structure classification prediction of the NCC S-wave velocity 3D model

Figure 2. Comparison map of seismic profile labeling and prediction

The imaging results were statistically accurate by the obfuscation matrix algorithm. Sample points, which has important implications for the overall accuracy evaluation of the results, were extracted according to the area measuring spots. Then, the sample points should be evenly distributed as far as possible to avoid amplification or omission of related problems. This method can objectively translate the overall precision of the crust structure in the study area. Fig.3 shows Classification accuracy of crustal structure and velocity structure.

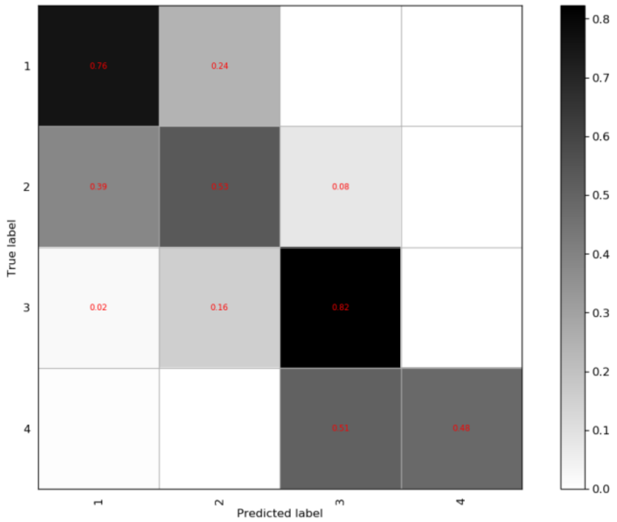

Figure 3(a) Classification accuracy of crustal structure longitude 114 profile

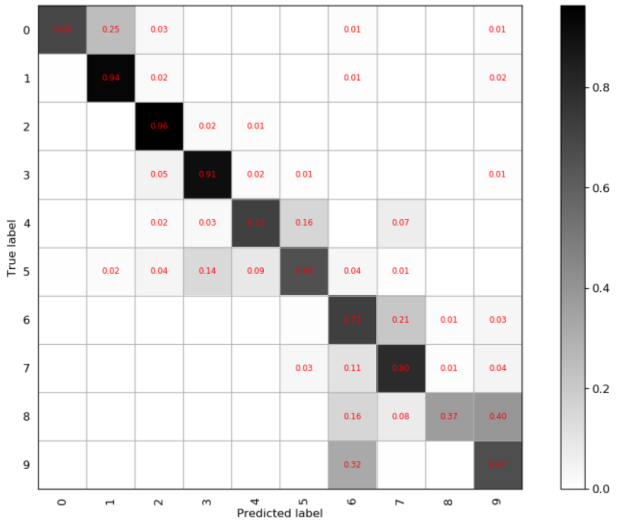

Figure 3(b) Classification accuracy of velocity structure longitude 108 profile

Figure 3. Accuracy verification of deep learning prediction results based on confusion matrix algorithm

4. Concluding Remarks

Based on the seismic interpretation images of the north China craton region including Crustal structure passive source detection profiles, wide-angle reflection/refraction profile of deep seismic sounding, a P-wave velocity 3D model section and a S-wave velocity 3D model section of receiving function method, deep learning method is used to classify and predict structural images of different seismic wave velocities. In velocity structure prediction, the errors caused by too many categories are the focus of future research. By verifying the accuracy of the results with the obfuscation matrix algorithm, it can be found that the deep learning method can automatically extract the information of the main discontinuity surface and the velocity structure, and this method could realize the classification and extraction of different geological structures in the crust.

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References

[1] Yang Y, *Research on anomaly volume modeling based on fusion segmentation*, University of Electronic Science and Technology of China, 2018.

[2] Ball J E, Anderson D T, Chan C S, A comprehensive survey of deep learning in remote sensing: theories, tools and challenges for the community, *Journal of Applied Remote Sensing*, **2017**, 11(4): 042609.

[3] Zhang L, Zhang L, Du B, Deep learning for remote sensing data: a technical tutorial on the state of the art, *IEEE Geoscience and Remote Sensing Magazine*, **2016**, 4(2): 22-40.

[4] Cheng G, Han J, Lu X, Remote sensing image scene classification: benchmark and state of the art, Proceedings of the IEEE. [S.l.:s.n.] **2017**, 105(10): 1865-1883.

[5] Duan Y H, Wang F Y, et al. Three dimensional crustal velocity structure model of the middle-eastern North China Craton (HBCrust1.0), *Science China Earth Sciences*, **2016**, 59: 1477–1488.

[6] Zheng T, Zhao L, Zhu R. New evidence from seismic imaging for subduction during assembly of the North China craton, *Geology*, **2009**, 37(5): 395-398.

[7] Jia S, Wang F, et al. Crustal structure and tectonic study of North China Craton from a long deep seismic sounding profile, *Tectonophysics*, **2014**, 627: 48-56.

[8] Zhu X X, Tuia D, et al. Deep learning in remote sensing: a comprehensive review and list of resources, *IEEE Geoscience and Remote Sensing Magazine*, **2017**, 5(4): 8-36.

[9] Mou L, Zhu X X. RiFCN: Recurrent network in fully convolutional network for semantic segmentation of high resolution remote sensing images, (2018-05-16). https://arxiv.org/abs/1805.02091.

[10] Zhao W Z, Du S H, Emery W J. Object-based convolutional neural network for high-resolution imagery classification. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **2017**, 1-11.

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