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Earthquake Distribution and Crustal Seismic Wave Velocity Based on Machine Learning

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Abstract: It is of great significance to accurately pick up the first arrival of P wave and S wave for the accurate location of earthquakes and the explanation of seismogenic mechanism. This paper focuses on the analysis of seismic distribution and seismic wave velocity of the bottom shell based on machine learning. In this paper, convolutional neural network is used to pick up seismic P and S waves when they first arrive. Compared with the traditional STA/LTA, the convolutional neural network method does not manually set thresholds and manually select feature functions, but only relies on convolutional neural network to automatically extract waveform features, and the model has good generalization. The research results of this paper can provide a new idea for picking up P and S waves at their first arrival in the future, so as to pick up P and S waves at their first arrival more accurately, and it is expected to provide technical support for the location of earthquakes and the explanation of seismogenic mechanism of earthquakes.

1. Introduction

Earthquake is an extremely serious natural disaster. It is a phenomenon that the crustal plates directly squeeze and collide with each other, leading to dislocation and rupture within the plates, and the earth shakes when the crust releases energy quickly. Earthquake itself is extremely destructive and can destroy buildings and other structures in a short time. In addition, secondary disasters such as tsunami, debris flow, fire and leakage of toxic and harmful substances, which seriously threaten people's life and property safety, will also be triggered [1-2]. China has a vast territory and is located between the Pacific plate and the Asia-Europe plate. Under the influence of the activities of the two plates, China has a high frequency of earthquakes and a wide range of distribution. Due to the large population and relatively concentrated distribution of population, once a big earthquake happens, it will cause serious loss of life and property to the people. According to scientific statistics, tens of thousands of earthquakes occur around the world every day. Many of them are not noticed by people because their magnitude is too small or their source and epicenter are too far away. However, several large earthquakes in recent history have made people all over the world aware of the danger of earthquakes [3-4]. In order to reduce the losses caused by earthquake disasters, seismological researchers have carried out a lot of studies on rapid earthquake reporting and earthquake early warning, among which the first arrival pickup of P wave (Primary wave) and S wave (Secondary wave) is an important basis of these studies. After an earthquake, there are two main types of waveform signals, one is called longitudinal wave, the other is called shear wave. The longitudinal wave, also known as the compression wave, is the first seismic waveform signal to arrive, and its propagation speed is fast and its damage is small. Shear wave, also known as shear wave, is the second arriving seismic waveform signal, and its propagation speed is slower than that of P wave, with strong destructibility [5-6].

Seismic wave at the beginning of P wave and S wave to the precise then pick up is an important part of the seismological monitoring, early at the beginning of P wave and S wave seismic waves to there is picked up by seismology experts, seismologists according to their own scientific experience through naked eye identification of seismic wave of P wave and S wave, this kind of method to collect high precision, but time-consuming, Moreover, it is greatly influenced by the subjective factors of seismologists [7-8]. With the development of technology, automated seismic phase picking technology has been gradually developed [9]. Some scholars have proposed an automatic velocity picking method based on convolutional neural network. Their proposed method formalizes the pickup problem as a ConvNet regression model that maps NMO-corrected seismic acquisition to velocity error estimates. They also proposed a data preprocessing technique to normalize shallow and deep reflections aggregated by CMP to the same time difference shape, a key factor for successful training. They developed an automatic velocity picking technique based on convolutional neural networks on prestack CMP track sets. The ConvNet regression model was introduced to map the NMO-corrected seismic acquisition to the velocity error estimation, and the network was trained using a predefined velocity range [10].

Relying on the rapid development of machine learning and computing power of computers, this research applies deep learning network to the research of speed picking, which greatly improves the computational efficiency while ensuring the accuracy of speed.

2. Seismic Wave Velocity Analysis Based on Convolutional Neural Network

2.1. Convolutional Neural Network

Convolutional Neural Networks (CNN) is a kind of deep learning network, which is distinguished from other networks by its unique convolutional layer. In general, it is composed of multi-layer networks, and each layer contains multiple planes composed of feature maps, which are composed of multiple independent neurons [11-12].

The core of convolutional neural network is convolution operation, which is equivalent to "filter operation" in image processing. For a convolution kernel (Filter) with the size of K*K, when it performs convolution operation on the image (Input) with the size of I*I, it is assumed that the Stride length of each convolution operation is S, and if the convolution operation exceeds the image boundary, the number of Padding pixels is P [13]. The feature map size of Output after such convolution is calculated as shown in Formula 1.

$$O = \frac{1 - K + 2P}{S} + 1 \tag{1}$$

After the feature Map is obtained by the convolution operation, how the subsequent network uses these feature maps needs to be explained. The introduction of this section focuses on the next pooling layer after the feature map. In theory, all the feature maps extracted from the convolutional layer can be used to train the classifier, but it is obvious that a huge amount of computation will be formed in the network [14]. In addition, if all the feature maps are used, the fitting effect of the network on the input data will be very good, while the fitting ability of the unknown data is lacking, which is the common phenomenon of Over-Fitting. To solve the two problems of heavy computation and easy overfitting, features at different locations can be clustered first, such as the average value in a region, so that the location information of the image can be obtained without losing when the features of lower dimensions are obtained. This clustering operation to obtain lower-dimensional features and improve overfitting is called Pooling [15]. The most commonly used method is maximum Pooling, but in addition to Max Pooling, there is also Average Pooling.

Activation function is one of the keys of all nonlinear neural networks. No matter how many layers the network has, without using the excitation function, the input of each layer node and the output of the upper layer node are linear [16]. This kind of network structure is the original Perceptron, and its fitting and approximation ability is very limited. Therefore, neural networks, especially deep neural networks, have strong fitting and expression ability only when they have nonlinear ability. In order to make the network have nonlinear capability, only using nonlinear functions between network layers can be realized. This is the function and ability of activation function [17].

The activation function used in this paper at the convolution layer is the reasonable Contractor Linear Unit (ReLU). Its analytic formula is as follows:

$$\mathrm{Re}\,LU = \max(0, x) \tag{2}$$

After the feature map is obtained in the pooling layer, it needs to use the traditional network structure for classification output. In the traditional network structure, all the nodes in the upper layer are connected to all the nodes in the next layer, and the network that forms the cross calculation weight is called the Fully connected layer (FC).

The output layer is the last layer in the network. According to the specific problem, the category can be output in the classification problem or a certain value can be output in the regression problem [18]. Typically, the output layer of the classification problem is preceded by Softmax activation functions that convert probabilities into categories.

2.2. Seismic Wave Velocity Analysis Modeling

Because the convolutional neural network in other fields of image processing applications have a lot of strong, such as image enhancement, target detection, face recognition, migration, etc., style and speed from seismic data modeling can also be bold as a special kind of image processing, and so the convolutional neural network decided to continue the use as a framework to build the convolutional neural network. In the following, the structure of the convolutional neural network and the selection of specific parameters are introduced in detail.

The overall structure of velocity modeling convolutional neural network designed in this paper is a simulation similar to nonlinear regression, rather than a judgment output. Different from the single-channel input, the input of the convolutional neural network is the picture of the seismic track set, and its meaning is "? Five single-channel input data of size 20X 100. The second layer is the convolution layer, whose format is [3, 3, 1, 32], followed by the same average pooling operation with size and step size of 2 X 2, so that the output of the second layer is [?, 10, 50, 32]. Be worth what carry is the size of a 3 X 3 convolution kernels is in all kinds of convolution neural network are common convolution kernels, because it is the smallest of throw 1 X 1 outside an odd number of convolution kernels, and the convolution kernels is an odd choice, there are two main reasons for this, is an odd number of convolution kernels ensures the anchor point (the center of the convolution kernels) coincide with image overlap among, Convenient sliding convolution; Second, in order to fill the zero operation, the two sides are still symmetric. The third layer is also the convolution layer, and the convolution format is designed as [5,5, 32, 64]. After the convolution operation and 2X2 pooling operation, the output format of the final layer is [?, 5,25, 64]. Although the output layer 3 convolution feature sizes for the extraction of 5 X 25 look there's still a lot of convolution space, but too much information compression is not conducive to the overall network performance boost, even the side effects, so the design of convolution operation only these, if you want more information, can increase the channel number to 128 or 256. Then the fourth layer is the fully connected layer, which is still used to rearrange the feature distribution values extracted by convolution into column vectors and connect them to 2000 neurons in the next layer, so it is expressed as [8000,2000]. Next, the fifth and sixth layers are similar fully connected layers, which are [2000, 1000] and [1000, 1200] respectively. The final output layer is [1200 1600] because the speed models we developed are all 40 X 40 grids. Will be 4, 5, 6, and the final output layer associated with observation can be found that this part of the structure appear similar to the shape of a funnel, such structure choice can understand first will be compressed, the eigenvalues of the convolution operation in the process of the compression automatically unwanted data, step by step, then gradually enlarge the good information, Finally get the desired output label.

3. Seismic Wave Velocity Analysis Experiment

3.1. Data Preprocessing

Original seismic waveform data directly from seismic stations by the instrument itself and other internal factors and external factors such as auto sound interference, so cannot be directly used for neural network training, must carry out a certain seismic data pre-processing, may only be used after the seismic waveform data are data pre-processing generally includes the following four points:

Delete abnormal data: In the use of seismic instruments are raw seismic waveform data acquisition, due to the instrument itself, occasionally leads to data collected by the abnormal peak or the condition of the missing data, when the seismic signal automatic identification will be mistaken for seismic signal (the coming of seismic signal waveform degree will have obvious increasing trend). Therefore, you need to delete the abnormal data.

Demean, delinear trend and waveform pinching. Seismic waveform data are one-dimensional time series data, so in a certain period, there will be linear trend or non-zero mean, which will directly affect the analysis of seismic data, and these situations need to be removed. When the filter is used to process the data, it is necessary to ensure that both ends of the data are zero; otherwise, there will be false spectral domain and the accuracy of the experimental results will be affected. Usually, researchers will solve this problem by pinch-out processing to ensure that the data gradually change to zero in the set area.

Filtering: Generally, the frequency of seismic data ranges from 0HZ to 20HZ. Therefore, waveforms in other frequency bands (low frequency band and high frequency band) need to be filtered to reduce noise interference.

Normalization: Normalization of data is beneficial to improve the efficiency of neural networks.

3.2. Experimental Environment

This paper is developed based on Center OS, using Python programming language, and using

Anaconda for version management. Anaconda has toolkit such as numpy, pandas, and matplotlib, which is an open source management tool of python. This paper uses the Ipython notebook integrated development environment under Anaconda for development. It is convenient and direct to read and display the results, which is suitable for the research and use of convolutional neural network in this paper. The algorithm framework of this paper is Tensorflow algorithm framework, and the convolutional neural network structure used in this paper is based on Tensorflow framework and Keras for training, testing and verification.

3.3. Evaluation Criteria

In this experiment, accuracy, precision, recall and average error are used as the evaluation criteria of the model to evaluate the pickup effect of P-wave and S-wave.

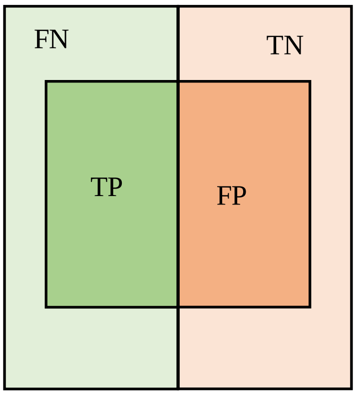

Figure 1. Relationship between FN, TN, TP and FP

Figure 1 shows the relationship between TP, TN, FP and FN.

Table 1. Confusion matrix definition

	Rreal value	N	P	S
Predictive value	N	TP_{NN}	FP_{NP}	FP_{NS}
	P	FP_{PN}	TP_{PP}	FP_{PS}
	S	FP_{SN}	TP_{SP}	TP_{SS}

In Table 1, TPnn, TPpp and TPss represent the noise, P-wave arrival time and S-wave arrival time that are correctly identified. FPnp represents P waves misidentified as noise, FPns represents S waves misidentified as noise, FPpn represents noise misidentified as P waves, and FPsn represents noise misidentified as S waves.

4. Analysis of Experimental Results

In this experiment, the traditional seismic phase recognition method STA/LTA and neural network were used to carry out the comparison test of recall, precision and F1 Score. The comparison results of the first arrival of seismic waves picked up by convolutional neural network and traditional method were shown in the following chart.

Table 2. STA/LTA results for P and S waves first arrival

	Precision P	Recall R	F1 Score
P	73.5%	61.7%	66.8%
S	51.7%	41.9%	43.6%

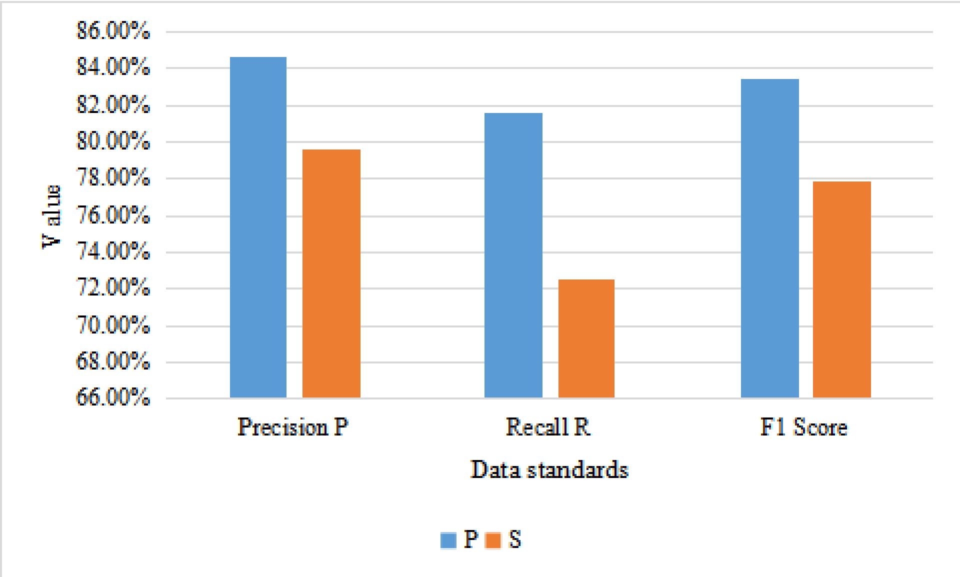

Figure 2. Results of neural networks for P and S waves first arrival

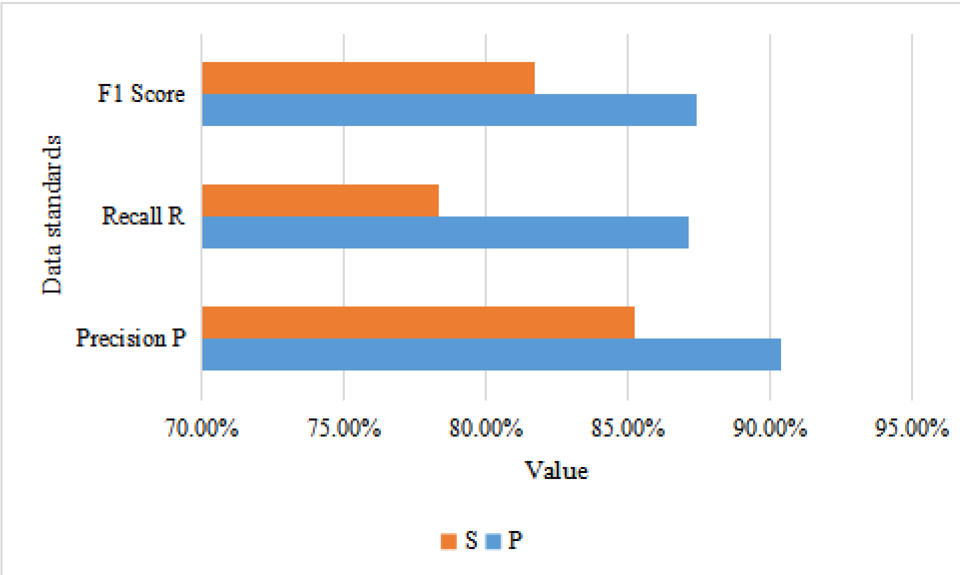

Figure 3. Results of convolutional neural network for P wave and S wave first arrival

According to the analysis of Table 2, FIG. 2 and FIG. 3, in terms of the precision of P-wave, the precision of convolutional neural network is 90.4%, 16.9% higher than that of STA/LTA, and 5.7% higher than that of neural network. For S wave precision, the S wave precision of convolutional neural network is 85.2%, which is 33.5% higher than that of STA/LTA, and 5.6% higher than that of neural network. In terms of recall ratio, for the recall ratio of P waves, the recall ratio of convolutional neural network is 87.1%, which is 25.4% higher than that of STA/LTA and 5.5% higher than that of neural network. For S wave recall, the S wave recall of convolutional neural network is 78.3%, which is 36.4% higher than that of STA/LTA and 5.8% higher than that of neural network. In terms of F1 Score, for P-wave F1 Score, the F1 Score of convolutional neural network is 89.4%, which is 20.6% higher than that of STA/LTA and 4.0% higher than that of neural network. For the F1 Score of S-wave, the F1 Score of convolutional neural network is 81.7%, which is 38.1% higher than that of STA/LTA and 3.8% higher than that of neural network. The performance of convolutional neural network is better than that of traditional STA/LTA and neural network models in three indexes.

5. Conclusion

In this paper, the relevant methods of convolutional neural network are used to solve the problem of the characteristic loss of the starting point and the low accuracy of the picking up of seismic waves P and S, and a model based on convolutional neural network is proposed. This model can recognize and pick up the P and S waves at their first arrival. Compared with the conventional STA/LTA, the improved model performs well in the three indexes of recall, precision and F1 Score. There are still deficiencies and improvements to be made in this paper. The model used in this paper is a relatively complex model, with many parameters involved in training and a relatively long training time. However, in the actual application of P wave and S wave picking up at the first arrival, the requirement of real-time is needed, so the efficiency of the network needs to be further considered.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Ferreira R S, Oliveira D A B, Semin D G, et al. Automatic velocity analysis using a hybrid regression approach with convolutional neural networks. IEEE Transactions on Geoscience and Remote Sensing, 2020, 59(5): 4464-4470. https://doi.org/10.1109/TGRS.2020.3022744

[2] Karimpouli S, Tahmasebi P. Physics informed machine learning: Seismic wave equation. Geoscience Frontiers, 2020, 11(6): 1993-2001. https://doi.org/10.1016/j.gsf.2020.07.007

[3] Wang W, Ma J. Velocity model building in a crosswell acquisition geometry with image-trained artificial neural networks. Geophysics, 2020, 85(2): U31-U46. https://doi.org/10.1190/geo2018-0591.1

[4] Fabien-Ouellet G, Sarkar R. Seismic velocity estimation: A deep recurrent neural-network approach. Geophysics, 2020, 85(1): U21-U29. https://doi.org/10.1190/geo2018-0786.1

[5] Moseley B, Nissen-Meyer T, Markham A. Deep learning for fast simulation of seismic waves in complex media. Solid Earth, 2020, 11(4): 1527-1549. https://doi.org/10.5194/se-11-1527-2020

[6] van den Ende M P A, Ampuero J P. Automated seismic source characterization using deep graph neural networks. Geophysical Research Letters, 2020, 47(17): e2020GL088690. https://doi.org/10.1029/2020GL088690

[7] Das V, Pollack A, Wollner U, et al. Convolutional neural network for seismic impedance inversionCNN for seismic impedance inversion. Geophysics, 2019, 84(6): R869-R880. https://doi.org/10.1190/geo2018-0838.1

[8] Titos M, Bueno A, Garcí L, et al. Detection and classification of continuous volcano-seismic signals with recurrent neural networks. IEEE Transactions on Geoscience and Remote Sensing, 2018, 57(4): 1936-1948. https://doi.org/10.1109/TGRS.2018.2870202

[9] Ross Z E, Meier M A, Hauksson E, et al. Generalized seismic phase detection with deep learningshort note. Bulletin of the Seismological Society of America, 2018, 108(5A): 2894-2901. https://doi.org/10.1785/0120180080

[10] Kamura A, Kurihara G, Mori T, et al. Exploring the possibility of assessing the damage degree of liquefaction based only on seismic records by artificial neural networks. Soils and Foundations, 2020, 61(3): 658-674.

[11] Woollam J, Rietbrock A, Bueno A, et al. Convolutional neural network for seismic phase classification, performance demonstration over a local seismic network. Seismological Research Letters, 2019, 90(2A): 491-502. https://doi.org/10.1785/0220180312

[12] Gogoi T, Chatterjee R. Estimation of petrophysical parameters using seismic inversion and neural network modeling in Upper Assam basin, India. Geoscience Frontiers, 2019, 10(3): 1113-1124. https://doi.org/10.1016/j.gsf.2018.07.002

[13] Dhanya J, Raghukanth S T G. Neural network-based hybrid ground motion prediction equations for Western Himalayas and North-Eastern India. Acta Geophysica, 2020, 68(2): 303-324. https://doi.org/10.1007/s11600-019-00395-y

[14] Mosher S G, Audet P. Automatic detection and location of seismic events from time‐delay projection mapping and neural network classification. Journal of Geophysical Research: Solid Earth, 2020, 125(10): e2020JB019426. https://doi.org/10.1029/2020JB019426

[15] Banerjee A, Chatterjee R. Mapping of Reservoir Properties using Model-based Seismic Inversion and Neural Network Architecture in Raniganj Basin, India. Journal of the Geological Society of India, 2020, 98(4): 479-486.

[16] Hammal S, Bourahla N, Laouami N. Neural-network based prediction of inelastic response spectra. Civil Engineering Journal, 2020, 6(6): 1124-1135. https://doi.org/10.28991/cej-2020-03091534

[17] Smith J D, Ross Z E, Azizzadenesheli K, et al. HypoSVI: Hypocentre inversion with Stein variational inference and physics informed neural networks. Geophysical Journal International, 2020, 228(1): 698-710. https://doi.org/10.1093/gji/ggab309

[18] Wamriew D, Pevzner R, Maltsev E, et al. Deep Neural Networks for Detection and Location of Microseismic Events and Velocity Model Inversion from Microseismic Data Acquired by Distributed Acoustic Sensing Array. Sensors, 2020, 21(19): 6627. https://doi.org/10.3390/s21196627