ISSN 2616-5767 Vol.5, Issue 10: 44-48, DOI: 10.25236/AJETS.2022.051008

Research on Application of Deep Learning Algorithm in Earthquake Noise Reduction

Wang Jinhuan[1,*], Ang Ling Weay[1] , Sellappan Palaniappan[1]

[1]Malaysia University of Science & Technology (MUST), Petaling Jaya, Malaysia
**wang.jinhuan@phd.must.edu.my*

Abstract: *For the traditional denoising method, it is necessary to accurately model the signal and noise and optimize and adjust the manual input parameters, which causes the problem that it is difficult to remove the noise of the seismic data. Especially random noise in remote areas has the characteristics of non-stationary, high energy, and serious aliasing of effective signals and random noise in the frequency domain, which brings great difficulty to the recovery of seismic data by conventional denoising methods, but the existence of random noise seriously affects subsequent earthquakes. The processing and interpretation of data makes it difficult to determine the exact location of oil and gas. It is necessary to develop an efficient denoising algorithm, which can retain the complex edge information and rich texture information of the signal as much as possible while removing random noise, so as to restore the seismic data and improve the utilization rate of the seismic data. In this paper, the convolutional neural network is applied to seismic data processing. The algorithm has a good denoising effect in seismic data. While eliminating a large amount of random noise, it retains the texture features in the data, realizes denoising of seismic data, and enhances vision quality.*

Keywords: *Seismic data, Convolutional neural networks, Denoising*

1. Introduction

In the exploration industry, oil and natural gas are both important economic lifelines of the country, and many industries are closely related to it. However, in recent years, surface resources have gradually become scarce, and seismic exploration has also developed into deeper and more complex geological conditions. Mining volume, it is necessary to strengthen the research in this area of seismic exploration. Seismic exploration refers to a geophysical exploration method that infers the nature and shape of underground rock formations by observing and analyzing the propagation law of seismic waves generated by artificial earthquakes by using the difference in elasticity and density of underground media caused by artificial excitation. It uses elastic waves excited by artificial methods to locate mineral deposits and obtain engineering geological information. Seismic exploration is the most important and most effective method to solve oil and gas exploration problems in geophysical exploration.

2. Theoretical Techniques

In seismic records, the denoising problem of random noise has always been a key research object in the field of exploration seismic data processing[3]. Random noise is represented by chaotic vibrations, with a wide frequency band and no definite apparent velocity. It is difficult to suppress random noise through noise estimation. In order to better remove random noise and analyze the characteristics of random noise in seismic data, a convolutional neural network structure is proposed to remove random noise.

2.1. Characteristics of Seismic Noise

The wavefield information obtained through seismic wave propagation is often composed of many signal components, such as reflected waves, direct waves, converted waves, and transmitted waves. These components contain a lot of rich information reflecting the properties of the subsurface medium. However, affected by external environmental factors and construction reasons, the collected seismic records are often polluted by random noise, and some seismic signal components are covered by other

ISSN 2616-5767 Vol.5, Issue 10: 44-48, DOI: 10.25236/AJETS.2022.051008

signal components. The observed seismic gathers all carry random noise and wavefield records of various component signals. Random noise (irregular noise) is a kind of interference wave that is inevitable in seismic exploration and does not have a fixed frequency and propagation direction. According to the causes of random noise, it can be divided into three categories: environmental noise, secondary noise and system noise.

2.1.1. Environmental Noise

Environmental noise is mainly composed of noise caused by natural external forces and power machinery. Natural external noise is the noise generated directly or indirectly by air movement. Power machinery noise is caused by some external mechanical interference during construction. For environmental noise, the interference of environmental noise can be reduced by adjusting the time to carry out construction when there are few people, improving the vigilance while shifting the location of the seismic signal receiving point, and burying the geophone deeper.

2.1.2. Secondary Noise

Secondary noise is a seismic wave generated during excitation and propagation in a medium. The characteristics of secondary noise are: the secondary noise varies with different underground media, and also changes with the change of excitation and reception factors. The suppression of secondary noise is extremely difficult, and secondary noise can be observed in the frequency domain, which is not a stable random process. Its energy intensity also increases with time and offset, which gradually degrades the quality of the seismic data.

2.1.3. System Noise

System noise is the noise generated during the working process of equipment such as seismic instruments, acquisition stations, and analog electronic tools. The characteristic of system noise is that the amplitude value of the same system noise is relatively stable under the influence of different frequency domains. According to the completely random characteristics of system noise, denoising can be performed by multiple superpositions.

2.2. Denoising Method

In order to provide high-quality seismic data, experts have studied and proposed many denoising methods for seismic data, most of which are combined with multiple methods, but the denoising effect is not ideal. Therefore, in order to improve the signal-to-noise ratio and resolution of seismic data, the denoising technology needs to be continuously improved. In this paper, an algorithm based on convolutional neural network is used to realize adaptive seismic data denoising. This denoising method is based on the self-adaptive learning data of the deep network to realize the multi-scale and multi-directional feature extraction of the network, so that the seismic data is more sparse, so that the detailed features of the seismic data can be obtained in more detail, and the seismic data can be removed better. Random noise in the data, preserving more valid signal.

At present, in seismic data processing, commonly used seismic data denoising methods mainly include transform domain denoising methods, filter denoising methods and comprehensive algorithm denoising methods.

2.2.1. Denoising Based on a Certain Transform Domain

Transform domain denoising is one of the most widely used methods at present, which transforms the seismic data collected by seismic exploration. The difference between the effective signal and the noise is observed in the transform domain, and the coefficients with the difference are reconstructed to achieve the effect of denoising. The most commonly used wavelet transform denoising method, although wavelet transform can perform a small amount of sparse representation for one-dimensional seismic data, and also has a good effect on sparse reconstruction of data, but it cannot be used for high-dimensional seismic data. expression. This transform domain-based denoising method needs to pre-select and fix the applicable parameters to convert the data to different domains for data processing, which makes the dynamic data structure lack adaptability.

2.2.2. Use Some Kind of Filtering for Denoising

First, a suitable filtering method is used to obtain the filtering factor in the filtering domain, and then the frequency spectrum recorded by the seismic set is convolved. Filtered seismic data denoising is often divided into three categories: frequency domain filtering, frequency wavenumber domain

ISSN 2616-5767 Vol.5, Issue 10: 44-48, DOI: 10.25236/AJETS.2022.051008

filtering, and spatial domain filtering. Commonly used filtering denoising techniques: median filtering, Wiener filtering, frequency filtering, f-k domain predictive filtering, F-X domain deconvolution, beamforming filtering, etc. When the noise level is high, denoising the seismic data using filtering method only erases the details and edge information of the seismic record, but does not remove the noise. This method has certain limitations, and it is difficult to achieve the best denoising effect.

2.2.3. Denoising Using a Comprehensive Algorithm

The combination of filtering and transform domain is used to realize a comprehensive algorithm. Clustering is carried out by using structural similarity in the spatial domain, and transformation is performed based on the clustering results to achieve a better low-ranking effect, which can well deal with the special characteristics of seismic data. feature that can accurately separate signal and noise. Commonly used comprehensive algorithm denoising techniques: polynomial fitting method, coherence enhancement method, singular value decomposition denoising method, anti-migration denoising method, independent component analysis, empirical mode decomposition, adaptive learning dictionary method, etc. However, the noise level in seismic data is often unevenly distributed, and the noise frequency band range is similar to that of the signal. These methods also only roughly remove the main energy of the noise. We hope to study a method that can adaptively eliminate random noise from seismic data, independently find the best solution, remove noise more thoroughly, retain more effective signals, and improve the quality of seismic data.

Applying convolutional neural network to seismic data processing is a new method to deal with random noise attenuation of seismic data.

3. Denoising Method Based on Deep Learning

Deep learning is a new end-to-end model, especially Convolutional Neural Networks (CNN) is an important branch of artificial intelligence. Convolutional neural network technology has been widely used in machine learning, data mining, image processing and other fields. In dealing with many problems, it has achieved results beyond human wisdom. In 1989, Le Cun was inspired by Hubel and Wiesel's research on cat visual cortex electrophysiology and proposed convolutional neural network (CNN). Convolutional neural network can directly learn the mapping between input and output, through convolutional layers and subsampling The feature extractor composed of layers extracts more abstract features in the data, so as to effectively solve complex nonlinear problems.

3.1. Convolutional Neural Networks

Research on seismic data denoising based on convolutional neural network, using Dn CNN network to denoise seismic data[1], using residual learning, batch normalization and adaptive moment estimation techniques, to achieve a deep convolutional neural network-based automatic Basic principles of adaptive seismic data denoising algorithms[4]. This is the basic idea of constructing the Dn CNN seismic data denoising model. Improve network denoising performance by optimizing network depth, training set and network parameters[2]. It has strong applicability in denoising of actual seismic data, and can remove a large amount of random noise in actual seismic data.

CNN is usually composed of one or more convolutional layers and is a deep neural network with a convolutional structure[5]. A typical CNN architecture consists of multiple layers, and the entire network consists of an input layer, a hidden layer, and an output layer. The hidden layer is composed of one or more pairs of alternately connected convolutional layers, pooling layers and fully connected layers to form a multi-layer feedforward network[6]. Each convolutional layer in the hidden layer consists of a set of filters. Each filter has a certain perceptual learning domain, which is also the key to learning to recognize the input data. The role of the pooling layer is to assist the existence of the convolutional layer, which reduces the spatial size of the convolutional data, reducing the network parameters and the amount of computation.

3.2. Characteristics of Convolutional Neural Networks

Convolutional neural network has high applicability in image recognition and image processing. Mainly because CNN has two important characteristics of sparse connection and parameter sharing.

3.2.1. Sparse Connections

The sparse connection is equivalent to multiple local perceptrons, which realizes the local filtering connection of the input data, which is characterized by being able to capture the texture features of all the data in the input data. In the process of connecting network layers to layers, traditional ANN uses matrix multiplication to connect neurons in two adjacent layers one by one, so that the network is connected layer by layer[7]. When using this connection method, with the increase of network depth, the number of nodes increases, resulting in a huge amount of calculation, making the network unable to train. The sparse connections of CNNs are equivalent to multiple local perceptrons, which focus on local connections. Make the sparse interaction between neurons and neurons, rather than one-to-one corresponding interactive connections. Therefore, sparse connections can effectively reduce the number of connections in the network, reduce the complexity of the network, reduce the amount of weight parameters that need to be trained in the network, and improve the computational efficiency.

3.2.2. Parameter Sharing

Parameter sharing means that in the same convolutional layer, the weights of different neurons connected to different positions of the previous layer of the network are equal. Therefore, neurons on the same feature channel have the same weight, which enables the network to achieve parallel learning and reduce the order of magnitude of parameters. The characteristics of parameter sharing are that it reduces network storage requirements, shifts layer invariance, reduces training complexity, and improves network efficiency. This feature is beneficial to improve the denoising efficiency of seismic data.

3.3. Propagation Algorithm of Convolutional Neural Network

The propagation algorithm of convolutional neural network mainly consists of two parts, namely forward propagation algorithm and back propagation algorithm. The forward propagation algorithm is to calculate the CNN model forward through a series of input layers, hidden layers, and output layers to obtain the output results[8]. Backpropagation algorithm, is the reverse calculation from the output layer, hidden layer, and input layer. In order to obtain the minimum error between the output results of the model and the actual results, the model is optimized by adjusting the parameter weights. Through the loop iteration of the two steps of forward propagation and back propagation, the weights between neurons are continuously updated to train the model, and the network with the minimum error value is obtained, and finally tasks such as prediction or classification are realized.

4. Conclusions

This paper mainly introduces the causes of random noise in the current seismic exploration process, and analyzes the characteristics of the noise. It also introduces several common methods for dealing with random noise, and analyzes the shortcomings of the common methods. Aiming at the shortcomings of traditional denoising methods, a convolutional neural network structure suitable for removing random noise is proposed. The relevant theory of convolutional neural network is introduced, the traditional structure of convolutional neural network is analyzed, the feature extraction process of convolutional neural network, the characteristics of sparse connection and parameter sharing in the network, and the algorithm for realizing network propagation are studied. The filter in the convolutional neural network can provide the optimal sparse representation of the local seismic event through the deep convolution operation of the network, and is effective in denoising the seismic data. It lays a foundation for the subsequent research on seismic data denoising algorithm.

References

[1] Shi Jun, Han Liguo, Yu Jianglong, etc. Seismic data denoising based on improved K-SVD dictionary learning method [J]. World Geology, 2018, 37(2): 627~635.

[2] Zhang Jianming, Zhan Zhicai, Cheng Keyang, Zhan Yongzhao. Research and development of deep learning [J]. Journal of Jiangsu University, 2015, 02: 191~200.

[3] Zhang K, Zuo W, et al. Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising. IEEE Transactions on Image Processing, 2017, 26(7):3142-3155.

[4] Das V, Pollack A, Wollner U, et al. Convolutional neural network for seismic impedance inversion [J]. Geophysics, 2018,2(3):2071-2075.

ISSN 2616-5767 Vol.5, Issue 10: 44-48, DOI: 10.25236/AJETS.2022.051008

[5] Qu Zhilin, Hu Xiaofei, etc. Research on Convolutional Neural Network Based on Improved Activation Function [J]. Computer Technology and Development, ISSN, 2017: 1005~3751.
[6] Sun Jun, He Xiaofei and others. Atrous convolution combined with global pooling convolutional neural network to identify crop seedlings and weeds [J]. Chinese Journal of Agricultural Engineering, 2018, 34(11): 159~164.
[7] Zhang Ligang. Image Semantic Segmentation Based on Fully Atrous Convolutional Neural Network [D]. Northeast Normal University, 2018.
[8] Xie Liang. Getting started with Keras: Python-based deep learning combat [M]. Beijing: Electronic Industry Press, 2017.