Scholar Publishing Group
Machine Learning Theory and Practice
https://doi.org/10.38007/ML.2020.010306
ISSN 2790-0983 Vol. 1, Issue 3: 45-52

Quality Control Method of Exploration and Development Data Based on Machine Learning

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Keywords: Machine Learning, Exploration and Development, Data Quality, Noise Reduction

Abstract: Because of increased exploration depth and increasingly complex geological environment survey area, makes the actual acquired seismic exploration data contains a lot of noise, the noise composition is serious interference signal effectively, affect the signal to noise ratio and resolution of the seismic data, reduce the quality of the seismic exploration data, to the subsequent inversion and interpretation, and finally brought difficulties such as oil and gas exploration work. This paper mainly studies the quality control method of exploration and development data based on machine learning. In this paper, the classification and source of desert noise are analyzed first, and a convolutional neural network with branch structure (BCDNet) is proposed to enhance the ability of extracting effective signal features from desert seismic exploration data, so as to better recover the seismic in-phase axis polluted by desert seismic random noise.

1. Introduction

Oil and gas resources are important raw materials for modern industrial production. The main way to obtain oil and gas resources is oil and gas field exploitation. Currently, most shallow or middle oil and gas fields have been developed in our country, and many oil and gas areas have been close to high water cut period, which need to develop more oil and gas fields urgently. Therefore, oil and gas exploration has turned to the deep and complicated geological environment of unconventional hydrocarbon accumulations, such as desert and basin and so on. Seismic exploration is a kind of geophysical exploration technology for oil and gas exploration. It mainly uses artificial excitation seismic elastic waves, receives seismic waves with acquisition instruments and records them in the form of data. After digital processing, seismic data are obtained, and geological structure information is obtained by analyzing the propagation law of seismic waves in the underground [1-2]. Seismic exploration consists of three steps: data acquisition, data processing and seismic data interpretation. The seismic signal containing geological information in seismic data is called the effective signal, and the signal that interferes with the recognition of the effective signal is noise. The purpose of seismic data processing is to separate the effective signal and noise in seismic data and obtain high-quality seismic data so as to obtain reliable geological information [3-4]. In recent years, machine learning has risen rapidly, showing superior performance in data processing. As a branch of machine learning, deep learning methods have been developed and increasingly mature, and have been applied in many fields, such as image recognition, image denoising, face recognition [5-6], natural language processing, etc. Developed from neural networks, deep learning is a method of feature learning driven by a large amount of data. Convolutional Neural Network (CNN) is a kind of feedforward neural network in deep learning algorithm, which has the ability of representation learning and strong data processing ability. Variational Auto-encoder (VAE) and Generative Adversarial Network (GAN) are generative models in the field of deep learning, which have strong generative ability. It performs well in processing complex high-dimensional data and has been successfully applied in the field of image processing [7-8].

Because the exploration environment is more and more complex, the seismic data collected have many kinds of noise and great intensity, and the effective signal is difficult to identify. In view of the difference between effective signal and noise properties of seismic data, experts and scholars at home and abroad have proposed many noise suppression methods for seismic data, which are mainly divided into traditional denoising methods such as time-frequency filtering, sparse transformation, modal decomposition and low-rank matrix decomposition, and intelligent denoising methods based on deep learning [9-10]. The traditional method can achieve certain effect in suppressing the noise of seismic data, but it has some limitations. These methods need to rely on manual prior knowledge to manually select parameters, and the denoising results have problems such as serious loss of effective signal amplitude, incomplete noise suppression and imprecision, etc. The processing efficiency of seismic data is low, which cannot meet the needs of processing massive seismic data. Therefore, more intelligent denoising methods are needed [11]. In recent years, deep learning methods have been applied to seismic data noise suppression. Some scholars have improved the original DnCNNs to suppress random noise in desert seismic data [12]. Some scholars put forward a new denoising algorithm based on deep neural network. Deep denoising device deals with white Gaussian noise, colored noise and non-seismic signals in seismic data [13].

This paper will deep learning method is applied in the field of seismic data noise suppression, analogy in image denoising, seismic data can be seen as containing complex noise image, network features automatic build by studying a large number of seismic data with noise in data denoising data mapping relations, processing speed is superior to the traditional method, and need not manual adjustment parameters, reduced the human intervention, Meet the requirements of modern seismic exploration processing massive data.

2. Noise Reduction in Desert Seismic Exploration Based on Neural Networks

2.1. Properties of Desert Random Noise

Noise in seismic exploration can be classified differently according to different ways. According to the propagation mode of noise in strata, noise can be divided into surface waves, multiple waves, refracted waves and side waves. According to the property of noise in exploration records, it can be divided into coherent noise and random noise. From the actual exploration records obtained by us, we know that the main noise in seismic records is random noise of low frequency, so this paper mainly analyzes and suppress random noise. In addition, a few effective signals in the records were submerged in surface waves, and we also analyzed the properties of the surface waves [14-15].

(1) Natural noise

Natural noise is the noise generated by non-human activities but natural environment, such as thunder, rain, wind and so on. Because of the high wind and sparse vegetation in desert areas, the natural noise is mainly caused by the wind force on the dunes. We also analyze the noise properties. From the F-K spectrum, it can be seen that the natural noise mainly exists in the low frequency band 0-30Hz, and from the single channel of natural noise, it also indicates that the amplitude of noise is large and the amplitude change is quite drastic. At the same time, the frequency of the effective signal mainly exists in the low frequency band, and the amplitude of the natural noise changes sharply, so the natural noise will seriously pollute the effective signal, which also indicates that the natural noise accounts for the main part of the random noise [16].

(2) Human noise

Humanistic noise refers to the noise produced by human activities. In our desert seismic exploration, there are mainly two kinds of human noise, in the distance of the geophone surveyor walking around or the work of the survey machine vibration, this kind of human activity noise is called near-field human noise; The noise of human activity at a relatively far distance, such as the driving noise of vehicles on a distant highway or the living noise of villages and towns at a distance, is called far-field human noise.

Because the human activity is far away from the detection point, the noise point of human noise is far away from the detector compared with the natural noise. And because there are few villages and vehicles in the desert area, the human noise mainly comes from the noise of the adjacent workers and machines, that is, the near-field human noise. From the single channel, it can be seen that the frequency of near-field human noise is larger than the amplitude of natural noise, but the amplitude change is not very drastic. Far field human noise mainly exists in high frequency band and its amplitude is small. In conclusion, human noise can pollute effective signals to a certain extent, and it mainly comes from near-field human noise [17].

(3) Surface waves

Surface wave is different from the above irregular noise, it is a regular noise, because the source is shallow in the process of exploration, the source propagates at the interface between earth and air to generate surface waves. Generally speaking, the large amplitude of surface wave indicates the strong energy of surface wave, and the bending of surface wave relative to the normal in-phase axis indicates the low propagation speed of surface wave. It can be seen from the single-channel amplitude-frequency curve that the frequency of front wave is also low, with the main frequency between 0-50Hz [18].

2.2. Bcdnet Denoising Network

In this paper, a desert seismic Random Noise Suppression network (BCDNet) with branching structure is proposed. The whole structure of BCDNet consists of two parts, denoising main network and branch network added to the subsampling layer of main network. Through the branch network, THE contextual features of seismic data are obtained in the early stage of the network, and the connection with the denoising main network enhances the ability of the main network to extract the effective signal features, and effectively realizes the suppression of desert earthquake random noise.

The main network adopts the same structure as FFDNet and mainly consists of two parts, one is the reversible Downsample layer (Downsample) and the inverse transformation layer (ReDownsample), and the other part is the convolution layer. Input was first desert seismic exploration data sampling layer under the reversible restructuring for half size, number of channels for four times under the mining of the raw data, data mining under way has two function, a function is through the study of branch network, output a seismic data context characteristics, another action is connected with the output of the branch network as the main network convolution of input layer, Achieve the purpose of denoising.

The reversible down-sampling layer of the main network is followed by the convolution layer, which adopts 15 layers, each of which is a combination of convolution (Conv), batch normalization (BN) and nonlinear activation function (ReLU). Specifically, the first layer is Conv+ReLU, and all the intermediate layers are Conv+BN+ReLU. The last layer is Conv. After passing through the convolution layer, the denoised downsampled data are reconstructed into pure seismic data with the same size as the input data through the inverse transform layer of the reversible downsampling layer.

In deep convolutional neural network, parameter update of each layer will lead to changes in the distribution of input data of the previous layer. Therefore, with the increase of network depth, the distribution of input data of the deep network will change greatly. When the number of network layers deepens, network training will be difficult and convergence will slow down. BN can normalize the input data of each layer to the standard normal distribution with mean of 0 and variance of 1. In this way, no matter how deep the network layer is, the input data will always be kept in the standard normal distribution, which can accelerate the speed of network training and convergence, prevent gradient dispersion and overfitting.

In the reversible down-sampling layer, the rows and columns of the noisy seismic data are first sampled at every other point, and after down-sampling, they are transformed into four down-sampling data of 250×30, that is, the size of the down-sampling data is halved. Secondly, the four down-sampling data of the size of the down-sampling data is spliced in the third dimension. The lower profile data with a size of 250×30×4 was formed. The inverse transformation of reversible downsampling, in contrast, reconstructs 500×60 clean seismic data from downsampled data that is halved in size and has four times the original number of channels.

The lower sampling data R is transformed into the reversible lower sampling layer, and the branch network learns the context feature E of seismic data through the lower sampling data R. The mapping function from the lower sampling data R to E is:

$$E = f_g(E:\theta_g) \tag{1}$$

Where, θg={Wg,bg} is the model parameter of the branch network, Wg is the weight of the convolution kernel of the branch network, and bg is the bias of the branch network. After learning the early context features, the branch network connects them with the lower profile data R and inputs them into the convolution layer of the main network, which maps the noisy data Y to the pure signal X. Thus, the mapping function of the main network can be written as:

$$F(Y;E;\theta) = \overline{X} \tag{2}$$

Where, θ={W,b} is the model parameter of the master network, the weight of the convolution kernel of the W master network, and the bias of the b master network. Substituting equation (1) into equation (2), the mapping function between noisy data Y and pure signal X can be obtained as follows.

$$F(Y;F_g(R;\theta_g);\theta) = \overline{X} \tag{3}$$

3. Noise Abatement Experiment of Seismic Data

In order to verify the effectiveness of the proposed Desert Seismic Random Noise Suppression Network (BCDNet) in de-noising DAS seismic data, this paper constructed a simulated DAS seismic record using the forward modeling method, and the relevant parameter Settings are shown in Table 1.

Table 1. Synthetic DAS record forward model

Parameter name	Parameter Settings
Seismic wave	Ricker wavelets
Seismic wave main frequency	60Hz
Well depth	1500m
Interval	1.5m
Sampling interval	0.0005s
Wave velocity	1500m/s-3000m/s

The Desert Seismic Random Noise Suppression network (BCDNet) proposed in this paper is applied to the denoising process of the simulated DAS seismic exploration records with noise. At the same time, we also selected some commonly used denoising algorithms to process the noise records of the simulated DAS so as to make a comparative analysis with the proposed algorithm BCDNet. These comparative experimental methods are: bandpass filter, f-x deconvolution and GAN(under the same training conditions as the proposed algorithm).

4. Analysis of Experimental Results

In order to quantitatively analyze the denoising ability and signal amplitude preserving ability of the four algorithms, the recorded signal-to-noise ratio (SNR) and mean square error (MSE) are calculated, as shown in Table 2.

Table 2. Four algorithms before and after denoising SNR and MSE

	Band pass filter	F - x deconvolution	GAN	BCDNet
SNR(dB)	5.7832	6.4093	9.8407	14.2376
MSE	0.0295	0.0227	0.0179	0.0049

From the table, we can find that BCDNet can obtain the maximum SNR and the minimum MSE at the same time, which also proves that the proposed method has excellent denoising performance.

In addition, three synthetic DAS noise-containing records with different noise levels were processed using the above four methods to measure the versatility of the denoising algorithm.

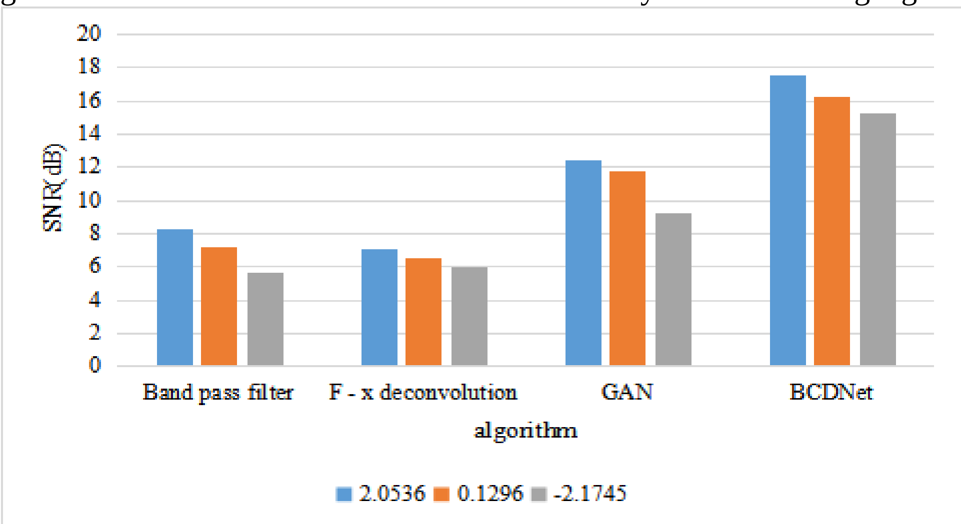

Figure 1. The denoising SNR(dB) comparison results were recorded at different noise levels

As shown in Figure 1, the denoising SNR comparison results are recorded for different noise levels.

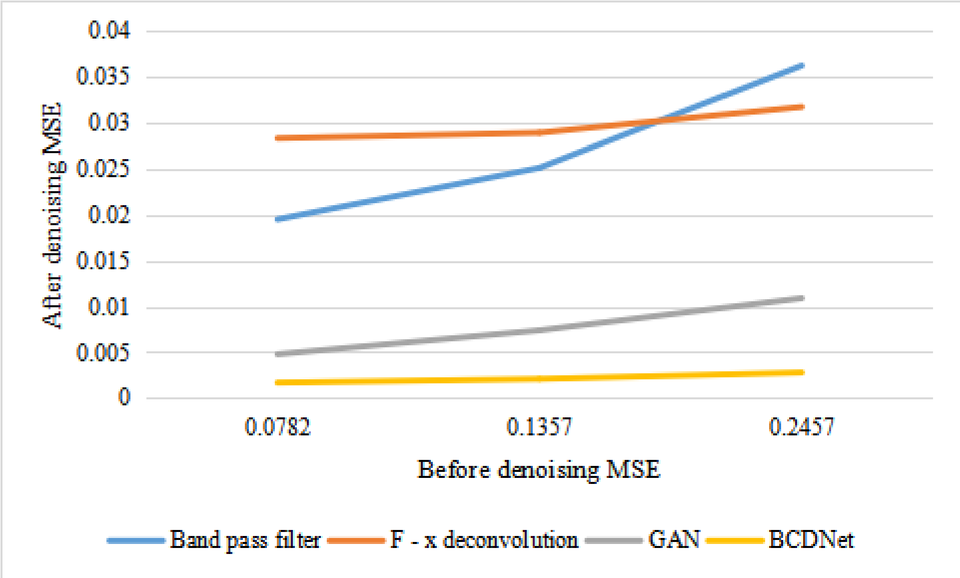

Figure 2. The contrast results of denoising MSE were recorded for different noise levels

As shown in Figure 2, the denoising MSE comparison results are recorded for different noise levels.

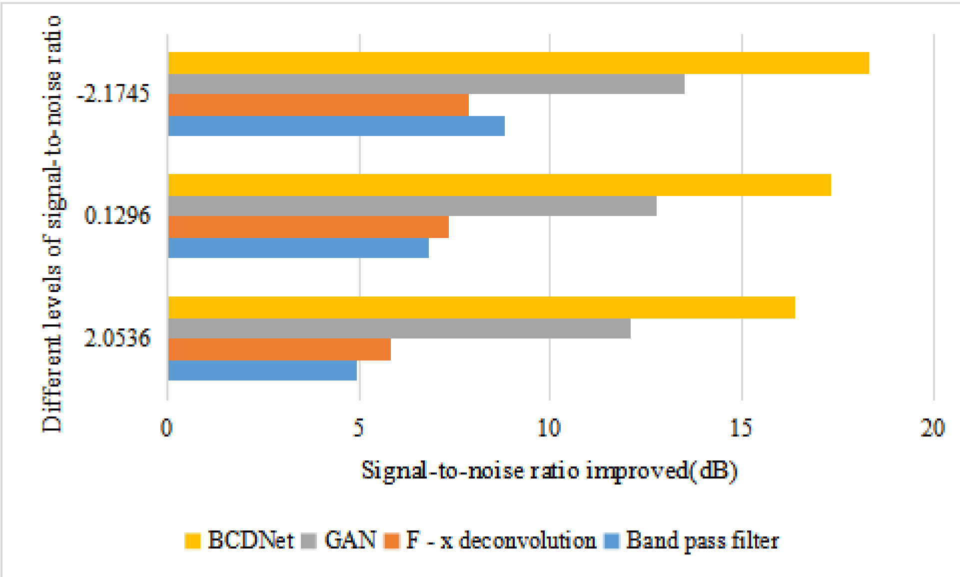

Figure 3. Signal-to-noise ratio increases were recorded at different noise levels

As shown in Figure 3, SNR growth data results are recorded for different noise levels.

As can be seen from the above chart, compared with the other three methods, BCDNet has more obvious advantages with better denoising ability and signal amplitude preserving ability.

5. Conclusion

Seismic exploration is an important means for the exploration of petroleum and other oil and gas resources, but the actual exploration process is often disturbed by noise information, affecting the quality of seismic data. Therefore, we need to carry out noise reduction processing for the received seismic exploration data, which is an indispensable important link in the process of seismic exploration. It is also the key to obtain geological understanding correctly in the subsequent work of seismic data analysis and interpretation. In this paper, a convolutional neural network with branching structure is proposed to suppress desert seismic random noise (BCDNet). BCDNet includes a branch network and a master network. The branch network learns the context features of the signal from the noisy data before the master network is denoised, and connects with the noisy data to guide the master network in denoising task. For algorithms related to deep learning, the quality of the training set directly affects the performance of the algorithm model. In this paper, the training set is modeled by the most basic seismic wavelet, and the stratum structure used is relatively simple and not accurate enough. In the following research, the actual geological structure information can be further studied, and more accurate exploration modeling methods can be used to improve the training set.

Funding

This article is not supported by any foundation.

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.

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