Seismic Lithofacies Computation Method Based on Deep Learning

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Summary

As we known, BP neural network which has been widely used in seismic lithofacies inversion has its own limitations, such as the local convergence, unstable results and inapplicability for large data sample. In order to overcome these limitations, a calculation method for seismic lithofacies based on deep learning is proposed in this paper. The proposed method can help to create a better resolution in inversion results and solve the prediction problem of complex lithology combined with the frequency division seismic data. Compared to BP-based method and conventional prestack elastic parameters inversion, it has a satisfactory effect in the anastomosis rate to the well points, coincidence with the geological understanding and the lateral continuity. This method was applied to the prediction of reservoir formation in a real field and its validity in seismic lithofacies calculation for the prediction of complex lithology has been shown.

Introduction

In seismic reservoir prediction, complex lithology predict is always a difficult point, such as calcareous mudstone in clastic rock、carbonate rocks and volcanic rocks etc (Li,2011; Lin,2002; Qi,2016). Now, the complex lithology prediction methods mainly focus on prestack elastic parameters inversion by intersection analysis of multi rock physics parameters (Peng, 2015). However, it's difficult to find sensitive and effective elastic parameters for some complex lithology scenes by this method, much less the postack inversion and attributes analysis. By another way, complex lithology prediction can be implemented by Wave-form clustering in which the relationship between waveform and lithofacies will be established (Hu, 2013). But the relationship between the actual lithofacies and seismic waveform is difficult to one-to-one match and the well-seismic calibration will result in multiple solutions. The nonlinear inversion method based on machine learning has been used to recognize complex lithology by calculating the characteristic curve, such as BP neural network, vector-support machine and so on(Zhang,2014;Wu,2009). However, these learning methods are easy to fall into the local minimum, unstable for inversion and unadoptable to large multiple data samples.

In recent years, the deep learning (DL), a machine learning, has been widely concerned home and abroad. With the aid of DL, a model with multi-layer structure can be used to mine the characters of massive data. The DL has promoted the development of speech recognition, vision recognition, target detection and many other fields. In seismic exploration, DL has been mainly focused on the rock image processing (Chen, 2016) and not related to complex lithologic identification.

Unmatched resolution between well and seismic is a main problem in the learning of conventional seismic attribute characteristic curve for complex lithology identification. So, we refer to a concept of seismic lithofacies (Liu, 2013) in order to solve the matching problem and extent traditional concept of lithofacies. Seismic lithofacies is a type of lithofacies that can be identified by seismic elastic parameters or seismic attributes. It can be divided by the recognition ability of lithology combination, elastic parameters of seismic inversion or seismic attributes. And seismic lithofacies can be calculated by both elastic parameters and artificial intelligence. The validity can be verified by Plane sedimentary facies.

The seismic lithofacies inversion based on DL aims to find out the relationship between the seismic attributes and coarsely-classified logging facies and then reduce the uncertainty of thin layer inversion combined with the reasonable utilization of the frequency information of seismic data in different frequency band, and finally obtains high resolution inversion results of lithofacies.

Method

The BP (Back Propagation) neural network is known as Multi-layer Perceptron and has been widely applied on seismic inversion. However, due to the shallow layer model in which only one hidden layer is adopted, BP has a few problems as following. The first involves the uncertainty of the inversion result caused by the single network structure and relative random construction of inversion model. The second relates the local convergence of the net because of the random initialization for neural network weights.

DL could, to some degree, alleviate the problem. It is a kind of machine learning process in which a multiple-levels deep network architecture can be created through certain training methods based on the sample data, first proposed by G. E. Hinton of the University of Toronto in 2006 (Hinton,2006; BENGIO,2009). In other words, the automatic extraction and classification of DL algorithms require low level or high level features. The high level features refer to the features can be graded dependent on other features. For example, in machine vision, the DL algorithm firstly learns the low level features from an original image, such as edge detection, wavelet filter, and secondly based on these low levels features creates new expressions through some methods like linear or nonlinear combination expression of these low levels features, and then repeat the process, finally obtains the high level features. At the same time the constructed model has the ability to represent large scale

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data because of the multiple levels, more model parameters, and sufficient capacity. So, for feature extraction of image and speech which is not obvious (always need manual design and have no intuitive physical meaning), the DL can achieve better results with large training data, and the feature extraction of seismic waveform also can benefit from this method.

The commonly used structures for DL contain the automatic encoder, sparse encoding, restricted Boltzmann (RBM), deep belief network (DBN) and convolutional neural network (CNN). The RBM model is a kind of energy model in which input data can be an effective projection since the data training process has a mild demand for the input data dimension (Hu, 2014). Due to the unsupervised learning based on RBM, the DBN works better than the stacked automatic encoder. CNN is an widely used image recognition method.

The DL for seismic fancies classification adopts the DBN model in this paper. First, the RBM unsupervised learning will be carried on the 70% of the known lithofacies and seismic attribute data from the bottom up layer by layer in the training process and the weight parameters of each layer of the network connection (shown in Figure 1).Second, the reverse training for network based on the test error of the remaining data (30%) will refine the connection weights, and ultimately the lithofacies learning DBN network will be determined (as depicted in Figure 2). So, the lithofacies in the whole range of seismic data could be calculated through this trained network.

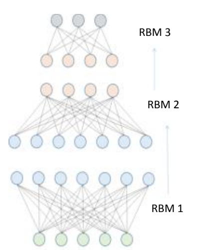

Figure 1: Training data layer by layer based on RBM unsupervised training

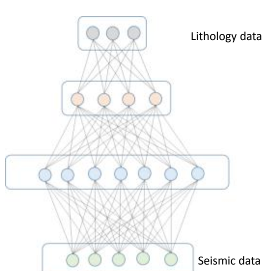

Figure 2: DBN network for learning lithofacies

A case of proposed method

Even the study area has been proved to be a place with a high possibility of hydrocarbon accumulation, but there are two problems to be paid attention to at present.

First, it is necessary to make clear the distribution range of the calcareous sandstone because of the development of the calcareous sandstone in the reservoir, which has a serious influence on the physical properties and the oil-bearing properties of the reservoir. But the lithology is diversified in work area, mainly including limestone, calcareous sandstone, sandstone and mudstone, among which limestone and calcareous sandstone shows high impedance characteristics and sandstone and mudstone shows low impedance characteristics. It is difficult to distinguish all kinds of lithology by single seismic attribute or inversion due to the complex lithological distribution.

Second, the lateral tip out of the sand body is related to the effectiveness of the trap, but the seismic resolution is relatively low and the conventional method is difficult to characterize the lateral distribution and tip off of the single sand body. As shown in Figure 3, Well A drills to the calcareous sandstone and is a dry layer, while Well B drills to the sandstone and is a gas reservoir. A lithological trap target is found between the two wells, and the lithological type of the target is the key to the evaluation of reservoir physical property. In addition, the target is located at the bottom of the structure; the well B has been drilled in the gas-water interface, so the upward pitchout of target lithology is the key to the formation of the reservoir.

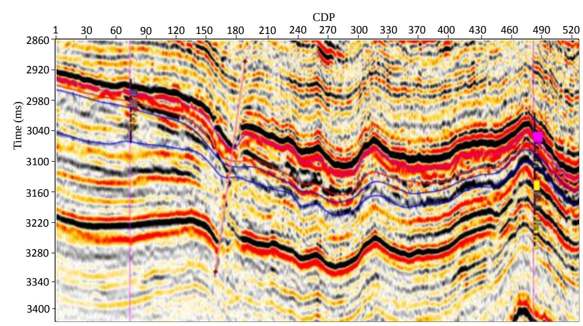

Figure 3: The original well-tie section of the key wells in the study area

Based on the above two problems, we believe that the prospection in this area should focus on the prediction of lithological classification and the characterization of sandstone boundary. Firstly, the neural network is carried out with the 20~50 Hz frequency of -90 degree seismic data as input and the logging interpretation of lithofacies as learning objective. And in order to contrast, inversion methods based BP and DL methods are implemented respectively. As described in Figure 4, after the well seismic calibration, the BP-based inversion result of lithofacies has a higher anastomosis rate to the well points, but the lateral performance is poorer, resulting in discontinuity of the seismic event and unclear boundary of the sand body. However, as shown in Figure 6, the DL-based facies inversion result shows the advantage of this method. It has a satisfactory effect both in the anastomosis rate to the well points and the lateral continuity. Besides, the sand body boundary becomes clearer and the distribution characteristics of sand bodies are in line with the geological understanding. According to the inversion results of DL, the target area is the sandstone deposit which is upward pitchout at higher part, and well B is two sets of oil-water interfaces. Figure 5 is the prestack lithofacies result section using traditional prestack impedance inversion. It is obtained with following two steps. First, inversion of prestack elastic impedance is calculated from the different angles, and then uses the coordinate rotation technology to linearly combine the radial elastic impedance from far and near angle. Compared to DL-based inversion section, this inversion result has two problems. One is that the distinction between lithofacies type is not clear enough, especially when it comes to the calcareous sandstone. The other is that its resolution is not as high as DL result, and is not conducive to the production due to complex calculation and larger error.

Conclusion

The DL-based method of seismic lithofacies has shown its effectiveness for complex lithology prediction. Its advantages lie on more stable inversion, global convergence and better inversion resolution that make conventional lithologic characteristic curve and seismic resolution more matched. In this method, more effective features can be extracted from large seismic data because of the depth structure network with multiple hidden layers and then used to create nonlinear connection to lithofacies for inversion. In the application to the real field, it helps to predict lithologic classification and describe sandstone boundary more accurately. The four lithology sets (limestone, calcareous sandstone, sandstone and mudstone) are effectively distinguished, and the distribution characteristics of sand bodies are in line with the geological understanding. In comparison to the traditional elastic parameters inversion and the BP neural network, the inversion effect of proposed method is superior. The practical application shows that the DL-based seismic lithology calculation has the value of production popularization in complex lithology prediction.

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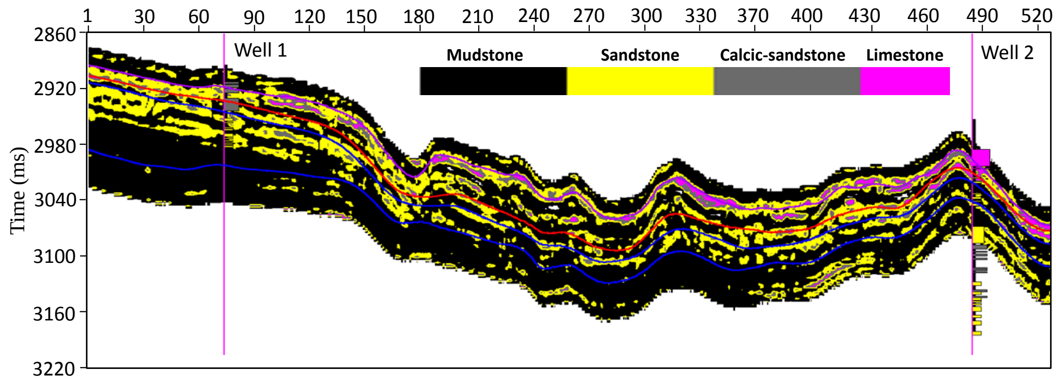

Figure 4: The lithofacies result based on BP

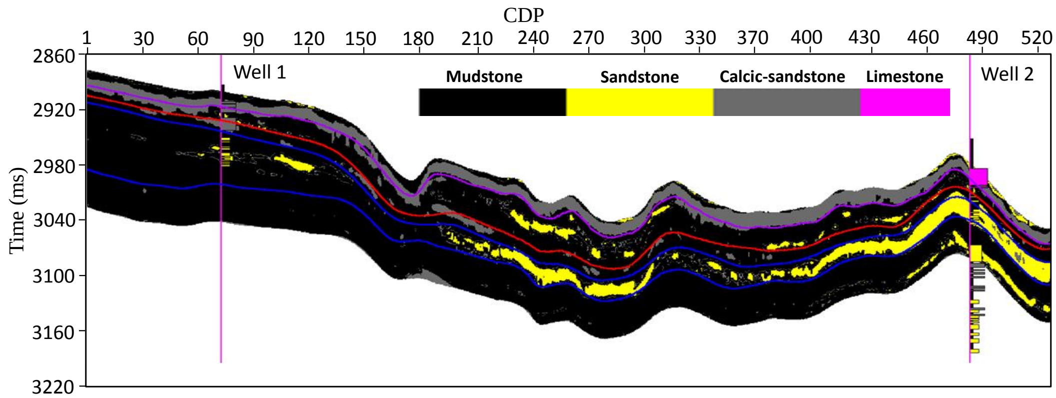

Figure 5: The lithofacies result based on traditional prestack impedance inversion

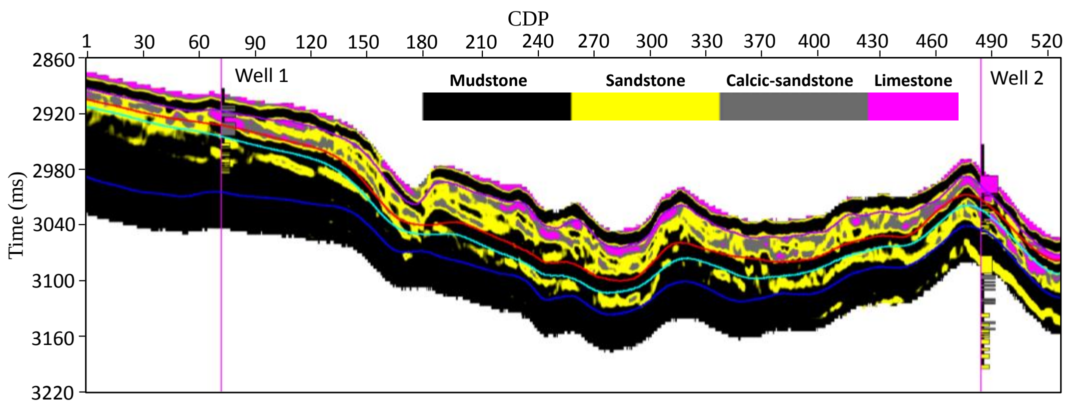

Figure 6: The lithofacies result based on DL