Seismic Facies Classification Using Bayesian Networks

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Summary

This article illustrates a novel approach (based on Bayesian Network. BN) for seismic facies classification. The approach, by integrated all available seismic attributes, could not only give the qualitative analysis of classification, but the quantitative analysis result of prediction probability of seismic facie. In addition, if we have more valuable experience from previous similar research, BN provide a useful tool for adding these experiences into BN Learning processing to improve the result of classification. For synthetic data with 30% random Gauss noise, the output of the method shows considerable agreement with the geologic model; similarly, for the real data application, the predicted facies match those results of previous research.

Introduction

In the past, seismic data have traditionally been used for identifying the structure of petroleum reservoirs. However, it is else hard to the subtle reservoirs exploring in the areas with the complicated geological conditions. So, for the requirement of reservoir prediction in target areas before the drilling, using various information to enhance the accuracy of reservoirs prediction have became hot issues in research of seismic interpretation field. So our purpose in this article is to introduce a new method of seismic classification based on BN, which could use many seismic attributes to identifying petroleum reservoirs efficiently.

Theory and Method

BN are probabilistic graphical models than represent a set of random variables for a given problem, and the probabilistic relationships between them. The structure of a BN is represented by a direct acyclic graph (DAG), in which the nodes represent variables and the edges express the dependencies between variable. The probabilistic part of the BN is represented by a set of conditional probabilities distribution (CPD) (Pearl, 1988). According the theory of BN, we design this workflow (Figure 1) to adapt seismic facies classification. The output is the result of seismic classification.

Examples

There is a typical outcrop of reef-shoal depositional system in Yijianfang Formation in western Tarim Basin, China, and the target zone in real seismic data has the same deposition environment in Tarim Basin. After detailed field geological survey and analysis of the physical properties measurements (including ultrasonic velocity and density) of rock samples, which are gathered from outcrop, at normal temperature and standard atmosphere in the laboratory, geological model has been constructed (Figure 2(d)). Figure 2(e) is the synthetic seismic data with 30% random Gaussian noise. Then we extracted eight seismic attributes has been extracted (including Root-Mean-Square Amplitude, Average Absolute Amplitude (Figure 3(a)), Instant Amplitude(Figure 3(b)), Instant Frequency, Absolute Distance, Euclidean Distance, Cross-correlation distance(Figure 3(c)) and Semblance Distance(Figure 3(d))). And then we choose some typical region of geologic model Figure 2(e) (white frame) and extract its correspondent attributes data to construct and train Bayesian classifier networks (Figure 4). Depending on learned BN, synthetic seismic data has been classified (Figure 5). For the result of seismic classification is matched with the geologic model, we could using this BN to classify the real seismic data. Depending on the learned BN, real seismic data has been classified (Figure 6). Seismic facies interpretation (Figure 6(a)) shows the space allocating relation of reef-shoal depositional system in real seismic data.

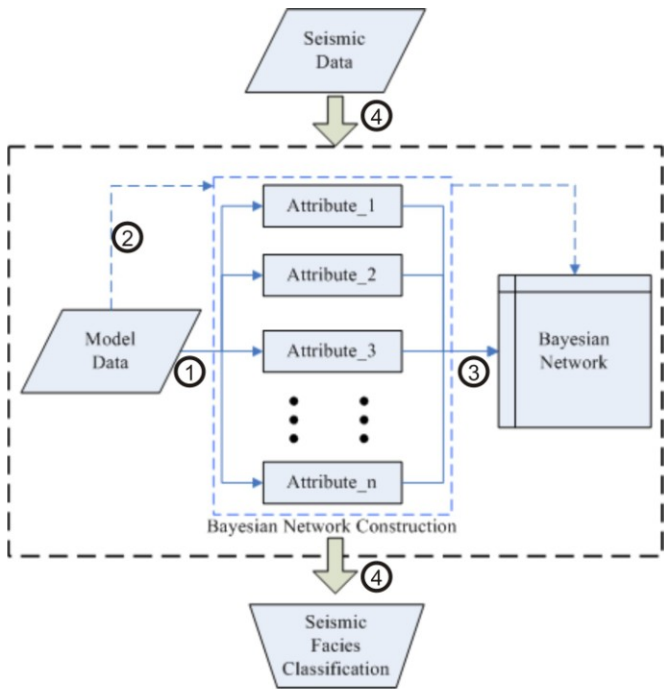


Figure 1: Generalized diagram of the workflow for Seismic Classification：

Step 1, Types of seismic attributes have been extracted from synthetic seismic data generated by geologic model, which is the result of field research and rock physical property measure.

Step 2, Training the BN. Some part of seismic data and there corresponding attributes data has been selected to training the BN model include construction and parameter.

Step 3, Using the rest data to test the classify model.

Step 4, Depending on this constructed BN model, all of those attributes, calculated by real seismic data, have been considered to classification.

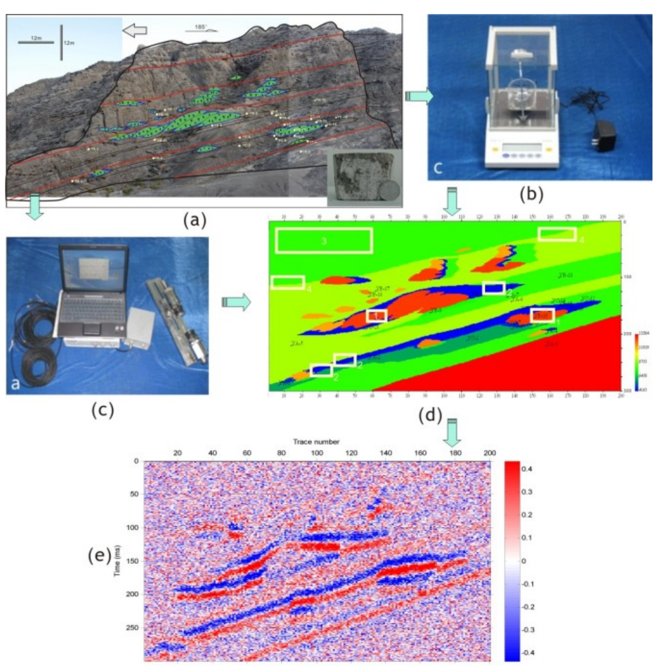


Figure 2: Example of application of seismic facies classification using BN on geologic model. (a)outcrop section (b)densitometer (c)wave velocity surveymeter (d)Wave impedance model (e)seismic section constructed from wave impedance model by generating synthetic seismic traces with zero-offset images rays and adding 30% random Gaussian noise.

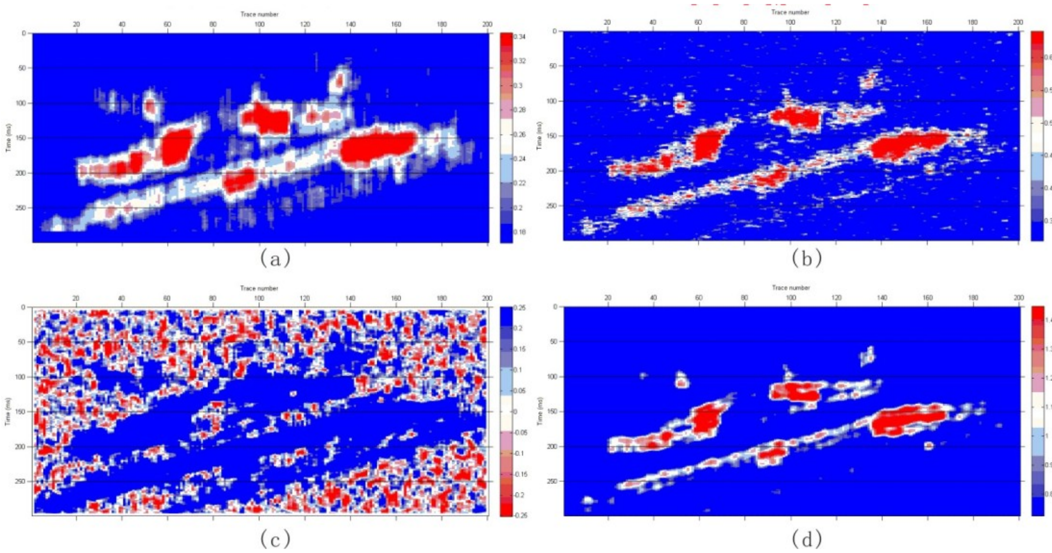


Figure 3: Seismic attributes: (a) absolute average amplitude; (b) Instant amplitude (c) cross coordinate (d) similar

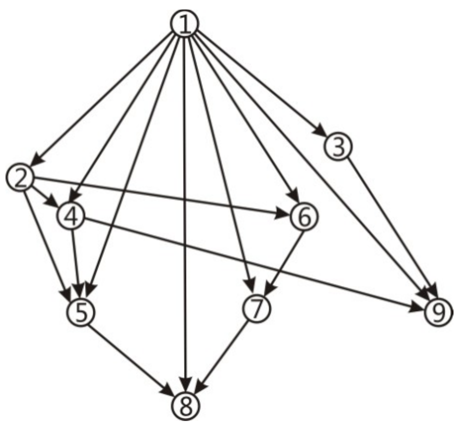


Figure 4: Construction of BN model: the construction is made by BN learning algorithm. ①, the root of network outputs the classify result. the rest node of network is its child node and directed edges demonstrate the Causality of each node. If tow nodes had not de connected by directed edges, they are independent mutually.

②Instant Amplitude, ③Instant Frequency, ④Root-Mean-Square Amplitude, ⑤Average Absolute Amplitude, ⑥Absolute Distance, ⑦Euclidean Distance, ⑧Cross-correlation distance, ⑨Semblance Distance

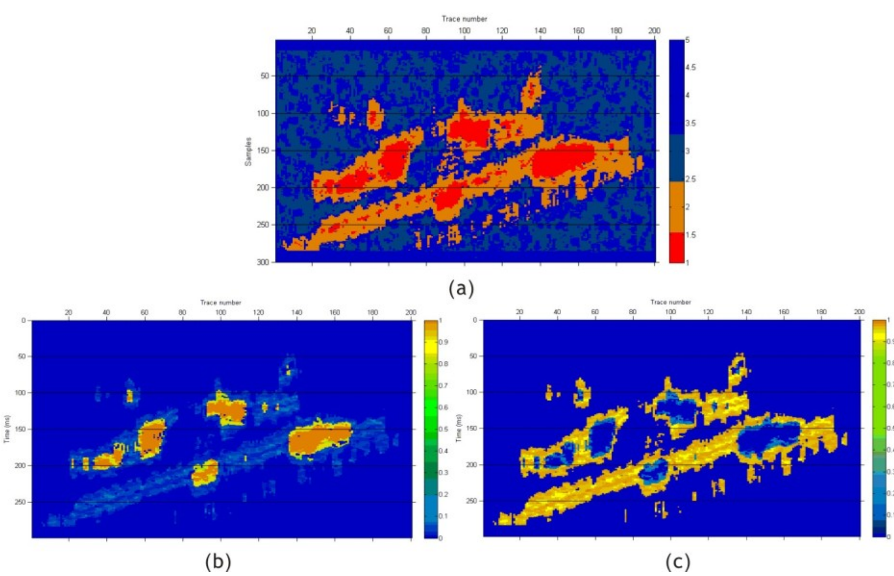
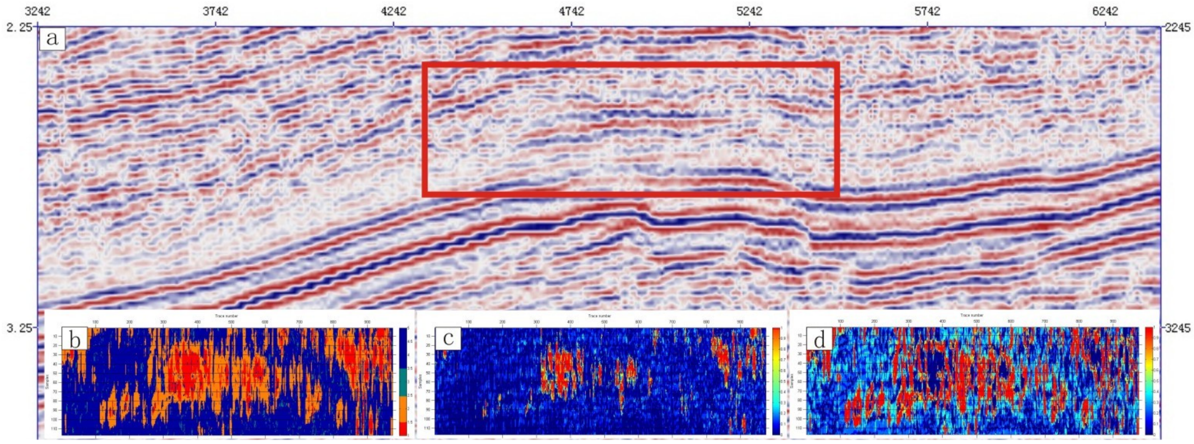


Figure 5: Result of the seismic classification using BN: (a) the result of seismic classification (1-5). Class NO.1 demonstrates reef facies, and class NO.2 demonstrates shoal facies. Those two pictures (below) show the prediction probability of class NO.1 (b) and NO.2 (c), which are our focus on. The high prediction probability is yellow.



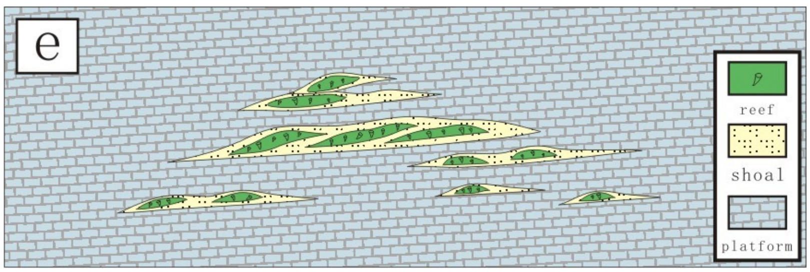


Figure 6: real seismic data and seismic facies classify result. (a)Seismic section of real data. (b)The result of seismic classification (1-5). (c) and (d) are the prediction probability of class reef and shoal. (e) is interpretation of seismic facies.

Conclusions

Test on geologic model and real seismic data shows the use of BN to classify seismic facies provides an efficient method, and this method could not only give the qualitative analysis of classification, but the quantitative analysis result of prediction probability of seismic facie. So the seismic interpreter can integrate more information to improve seismic facies interpretation result than other method.

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