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Application of Support Vector Machine in Porosity Prediction of Carbonate Reservoirs

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Abstract

Because the shape of the pore has a great influence on the longitudinal wave velocity of the rock, and the pore types of the carbonate rock are diverse, including primary pores, dissolved pores, caves, cracks, etc. Therefore, the wave impedance of carbonate reservoirs is controlled by both porosity and fracture porosity. Generally, the pore content of cracks is difficult to predict, so the porosity cannot be calculated under the condition that the wave impedance is known and the pore content of the crack is unknown. We introduce a data-driven approach, using support vector machine technology, taking the seismic properties of the wave impedance and the degree of crack development at the well point as input data, using the porosity as the prediction target, training the machine learning model, and then applying the model to the whole. In the study area, the porosity distribution of the study area is coming out. This method has achieved good results in the prediction of porosity of carbonate reservoirs in an oil field in Tarim Basin.

Keywords: Carbonate; Porosity; Wave Impedance; Crack; Support Vector Machine.

1. Introduction

A key step in calculating oil and gas reserves is to obtain accurate reservoir porosity. Usually, the step of calculating the porosity is to first use the 3D seismic data and the drilling data to perform the wave impedance inversion to obtain the wave impedance information of the reservoir. Then, based on the drilling data, the conversion relationship between the wave impedance and the porosity is established, and the wave impedance is converted into the porosity.

For conventional clastic reservoirs, the rock longitudinal wave velocity and porosity generally have a good negative correlation, so the conversion relationship between wave impedance and porosity can be established by the fitting formula method. However, for carbonate reservoirs, the fitting formula method will cause large errors.

Figure 1 is a plot of wave impedance and porosity of the Ordovician carbonate reservoir in an oilfield in the Tarim Basin, of which the data is from logging. It can be seen that the higher the porosity, the smaller the wave impedance, but the data points are scattered, and it is impossible to establish a suitable wave impedance-porosity fitting relationship with less error. This is due to the diverse pore types of carbonate reservoirs, including primary pores, dissolution pores, caves, and fractures. The combination of various pore types is complex, which makes the carbonate reservoirs have strong heterogeneity (Fig. 2).

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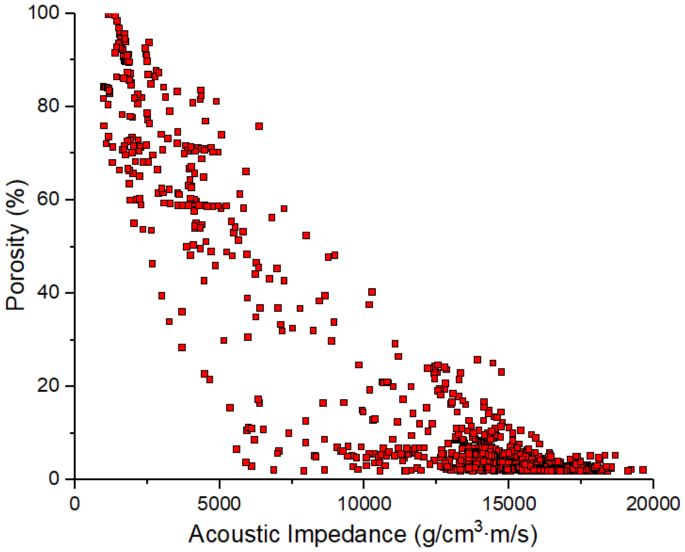

Fig. 1. Wave impedance-porosity intersection diagram of carbonate reservoir

Fig. 2. Carbonate pores are diverse in shape

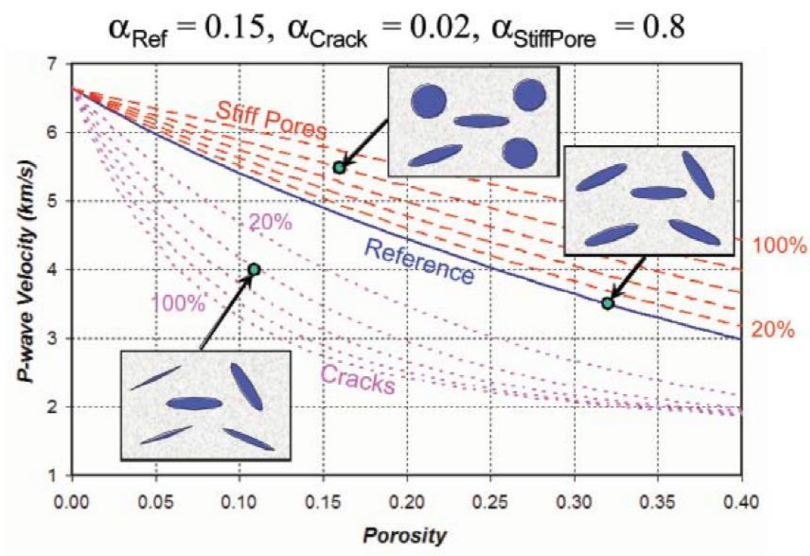

Fig. 3. Effect of different shape pores on velocity-porosity (Xu & Payne, 2009)

Previous studies have shown that pores of different geometries have a greater influence on the longitudinal wave velocity of rock [1-3]. Xu & Payne simulates pores of various shapes with ellipsoids of different flattening ratios (the ratio of the short axis to the long axis of the ellipsoid) [4]. The results show that when the flattening rate is small, that is, the pore shape is close to the coin shape, the longitudinal wave velocity decreases more rapidly as the porosity becomes larger (Fig. 3). The crack can be regarded as a small flattening pore, so in the pore space, the amount of crack has a great influence on the reservoir wave impedance-porosity relationship. This is why the data points in Fig. 1 are relatively scattered and it is difficult to establish a fitting relationship. We must know the content of the cracked pores to determine how the wave impedance changes with porosity.

For a three-dimensional research area, all of our reservoir information is derived from 3D seismic data and drilling data. If there is a wide azimuth prestack seismic data, we can predict the crack content by the azimuthal anisotropy method. However, such methods require high seismic data acquisition density and signal-to-noise ratio, which is usually limited by data acquisition costs. Very few oil fields have such high-quality data. Most oilfield pre-stack seismic data is of poor quality and cannot meet crack prediction. Claim. Therefore, in the case where the crack content cannot be accurately predicted, we must find other methods to achieve the purpose of porosity prediction.

The degree of fracture development is related to the degree of fracture of the rock, and the degree of fracture is related to the degree of fracture and stratum curvature. Therefore, the fault development or the degree of stratigraphic bending is large, and the more the rock is broken, the denser the crack. So cracks usually develop near faults and folds. We can describe the degree of crack development by using seismic attributes that can indicate the degree of fault and stratigraphic bending, such as curvature, dip, and so on. These seismic attributes can be calculated directly from the post-stack seismic data. They are related to the degree of crack development, but still can not quantitatively reflect the crack content. So we use a machine learning method, namely support vector machine technology. It trains a machine together with the wave impedance and crack attribute data related to porosity. Learn the model to predict porosity.

2. Support Vector Machine

Support Vector Machine (SVM) is a machine learning algorithm proposed in the early 1990s [5]. The principle is to map the linearly inseparable samples in the sample space to the feature space through the kernel function, and make the original linear indivisible samples linearly separable in the feature space, thus achieving the purpose of classification. The equation $f(x)$ that defines the optimal classification hyperplane is

$$f(x) = \mathbf{W}^T \varphi(x) + \mathbf{b} \tag{1}$$

Where $\mathbf{W}$ is the matrix of weight coefficients; φ is the normalization function; x is the sample data; $\mathbf{b}$ is the coefficient matrix.

Support Vector Regression (SVR) does not divide the sample into two categories, but minimizes the total distance from the sample to the plane on both sides of the optimal classification plane to achieve the fit. The definition error tolerance range is ε, the i-th relaxation factor is ξ_i, the penalty coefficient is C, and n is the number of samples, so the problem is transformed into the minimum value of the objective function, and the objective function is

$$\mathrm{C}\|W\|^2/2 + C\sum_{i=1}^{n}\xi_i \tag{2}$$

In this study, based on the principle of support vector regression machine, porosity prediction is performed by the complex nonlinear relationship between logging porosity and wave impedance and seismic properties of cracks.

Optimization of parameters is critical to improving the performance of the model. According to previous research experience [6, 7], the support vector machine kernel function is chosen as a Gaussian kernel function. Therefore, the fitting accuracy of the support vector machine regression model mainly depends on the selection of three parameters such as the insensitive loss coefficient ε, the penalty coefficient C and the width coefficient σ. In this study, the particle swarm optimization algorithm was used to optimize the parameters. Particle Swarm Optimization (PSO) is a group intelligent optimization algorithm proposed by Kenned and Ebermart in 1995 based on the social behavior of flocks and fish stocks [8]. The position of each particle of the particle swarm represents a potential optimal solution of the problem. Each particle has two characteristics of position and velocity. The objective function value corresponding to the particle position coordinate is used as the fitness value of the particle. The algorithm uses the fitness to Measure the pros and cons of particle position. The algorithm first randomly initializes a group of particles and then finds the optimal solution by iteration. In each iteration, the particle updates its position by tracking two extremums, one is the most position found by the particle itself, i.e., the individual extremum p; the other is the optimal solution currently found by the entire particle swarm, i.e., the global extreme value g. After the particle finds the above two extreme values, it updates its position and speed, and repeats the above process until the algorithm converges.

3. Application Case Analysis

The research area is located in an oilfield in the Tarim Basin. The target layer is the Ordovician carbonate karst fracture-cavity reservoir. The wave impedance and porosity data at the well point have been obtained from the well. The wave impedance data volume in the 3D work area has also been obtained from seismic inversion (Fig. 4, Fig. 5), and it is desirable to calculate the porosity distribution of the reservoir for the reserve calculation. Based on the previous analysis, we first need to calculate the seismic properties that describe the degree of fracture development. The attributes we choose include: maximum curvature, formation dip, seismic coherence, symmetry.

Formation dip [9]: From the perspective of geometric seismology, any reflection point on the 3D seismic region can be regarded as a time scalar field. The gradient of the scalar field reflects the fluctuation rate of the reflection surface, that is, the variation of the reflection surface in different directions. The formation dip attribute represents the first derivative of the seismic reflection surface in the direction of the fastest change. Through the calculation of the maximum dip property, it is possible to find and detect the characteristics associated with the tectonic deformation and predict the tiny crack development trend zone (Fig. 6).

Maximum curvature [10, 11]: A point on a surface has a curvature value in any direction, where the curvature defined by the plane orthogonal to the surface is called the normal curvature. In the infinite normal curvature, the largest absolute value is called the maximum curvature. The relative motion of the formation block is easily seen on the time slice of the maximum curvature data. The curvature property quantifies the angle of the curve offset line, which helps to dilute the local dip effect, emphasizing linear features associated with sedimentary features or small-scale faults. Combining these quantitative descriptions of the degree of structural bending with existing prior knowledge of the structure can be combined with geological models to predict natural fractures in the reservoir (Figure 7).

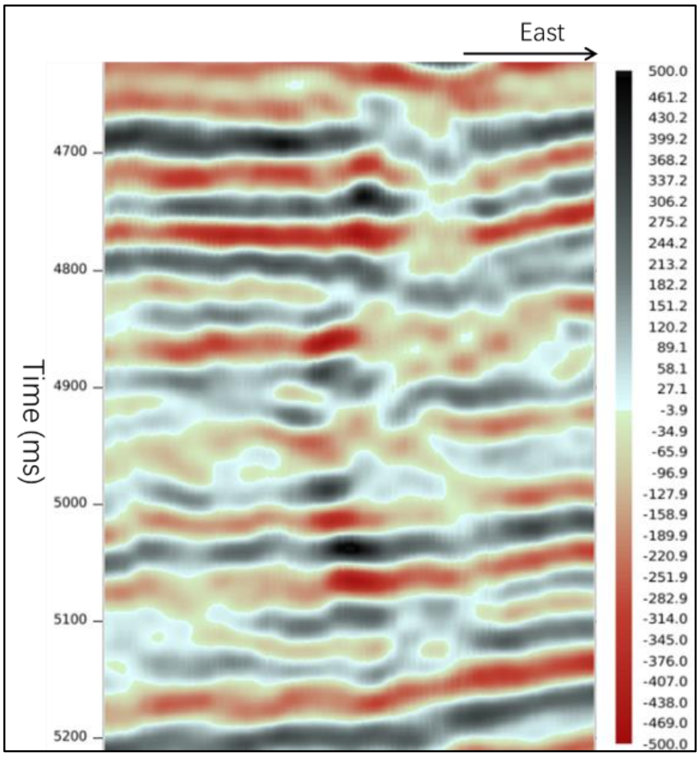

Fig. 4. 3D seismic section of the study area

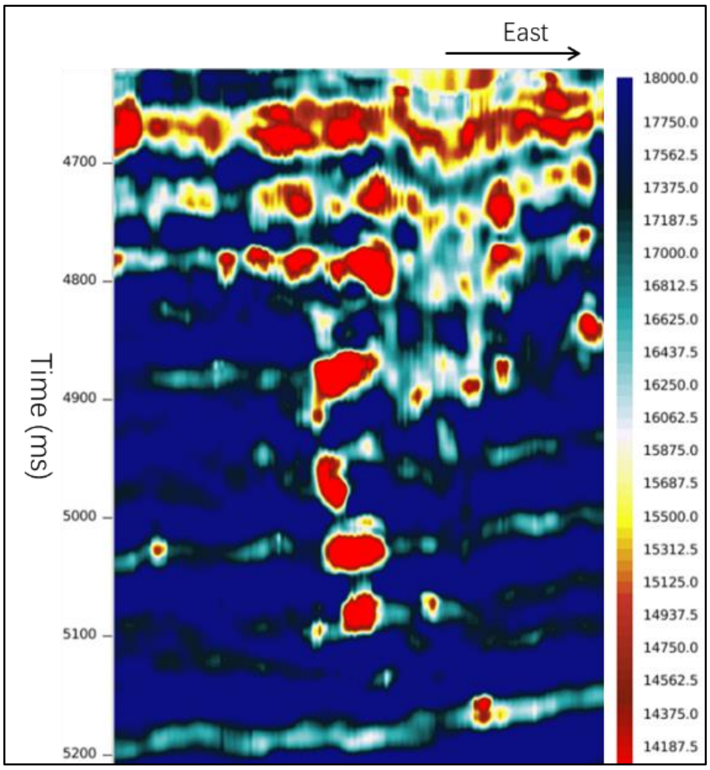

Fig.5. Study area wave impedance profile

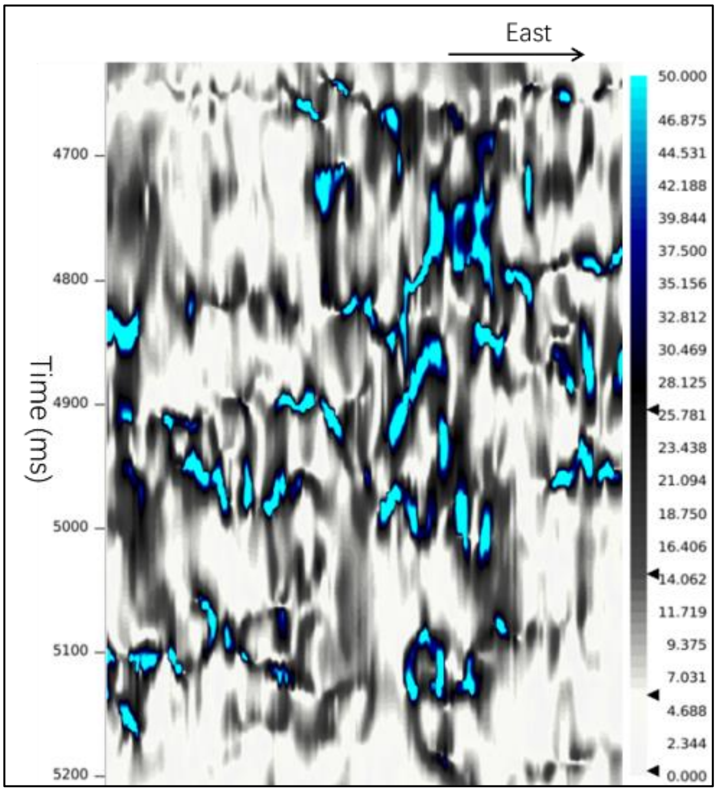

Fig.6. Formation dip profile of the study area

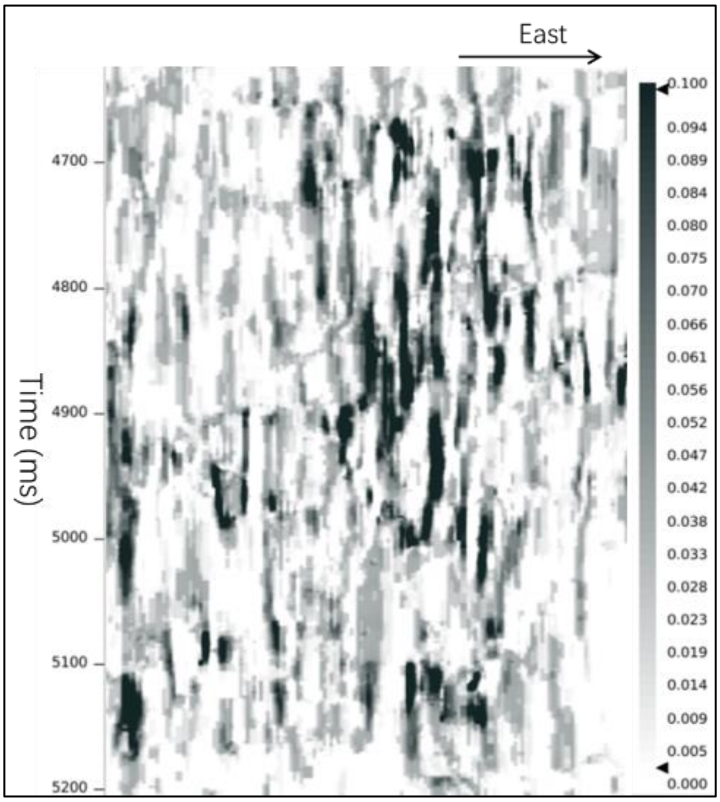

Fig. 7. Maximum curvature profile of the study area

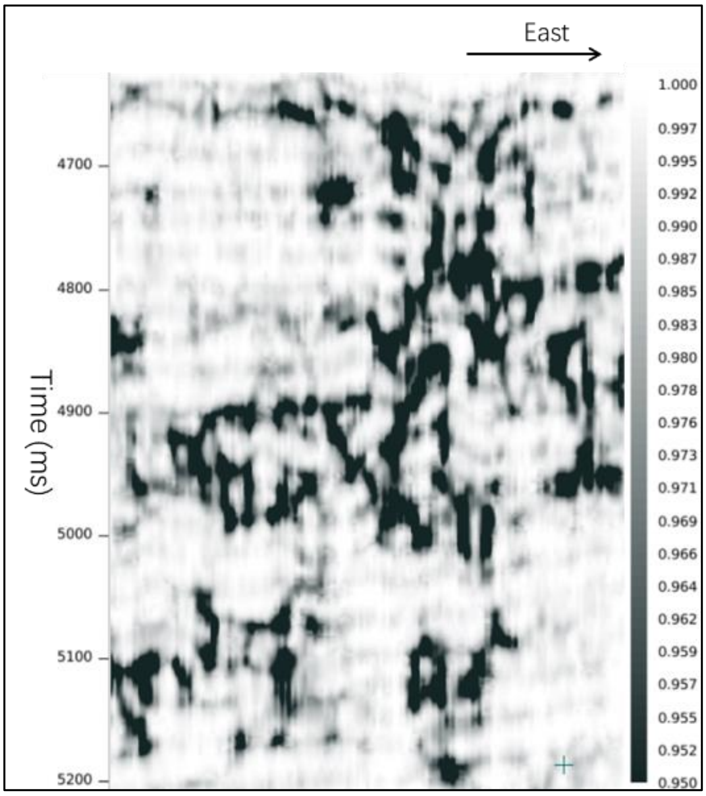

Fig. 8. Coherent analysis profile of the study area

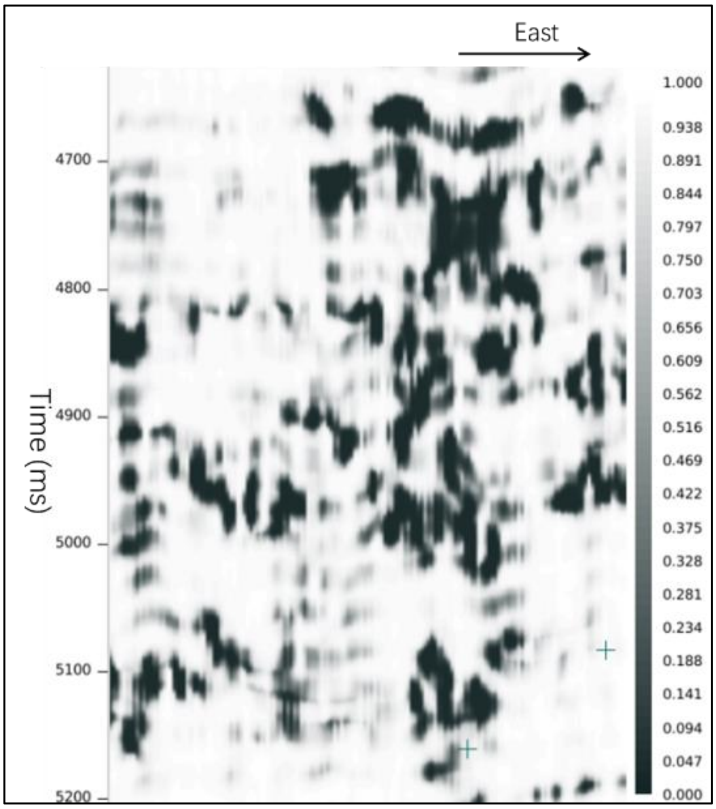

Fig. 9. Study area symmetry analysis profile

Coherent analysis [12]: The purpose of calculating the seismic coherent data volume is mainly to seek and share the seismic data to highlight those irrelevant data. Estimates of the three-dimensional seismic correlation can be obtained by calculating the local waveform similarity in the longitudinal and lateral directions. In the small range of faults, stratigraphic lithology mutations, and special geological bodies, the waveform characteristics between the seismic traces change, which leads to a local correlation between the track and the channel (Fig. 8).

Symmetry analysis [13]: According to the research on the sequence of reflection coefficients obtained from sonic logging and density logging, the series of seismic reflection coefficients conform to the generalized Gaussian distribution. According to the linear system theory, when the input signal is a stationary random process, the output is still a stationary random process. In particular, if the input is a stationary Gaussian process, the output is still a Gaussian process. That is, the linear transformation does not affect the random process. Distribution characteristics. The convolution model of the reflected seismic trace is a typical sliding average linear system model. If the seismic reflection coefficient sequence is regarded as a generalized Gaussian input signal, the output (seismic channel) should be the same distributed stationary signal, where the seismic wavelet It is considered to be the transfer function of the system. In the case where the formation is evenly layered, the actual seismic signal is a zero-mean near-symmetric generalized Gaussian distribution. However, when the nature of the local medium is abrupt, such as the pore-dissolved area of faults, rivers, and carbonate rocks, the seismic record will no longer satisfy the symmetric generalized Gaussian distribution, and the symmetry analysis can detect this asymmetric and non-Gaussian Changes can identify the mutated region of the nature of the subsurface medium (Figure 9).

Fig. 10 is a flow chart of a support vector machine predicting porosity. Firstly, the measured porosity of the well is used as the prediction target, and the machine learning model is trained by taking the properties of the wave impedance at the well point and the inclination of the formation as input variables. Then, the attribute data body of the 3D work area is input into the machine learning model, and finally the porosity prediction result is output.

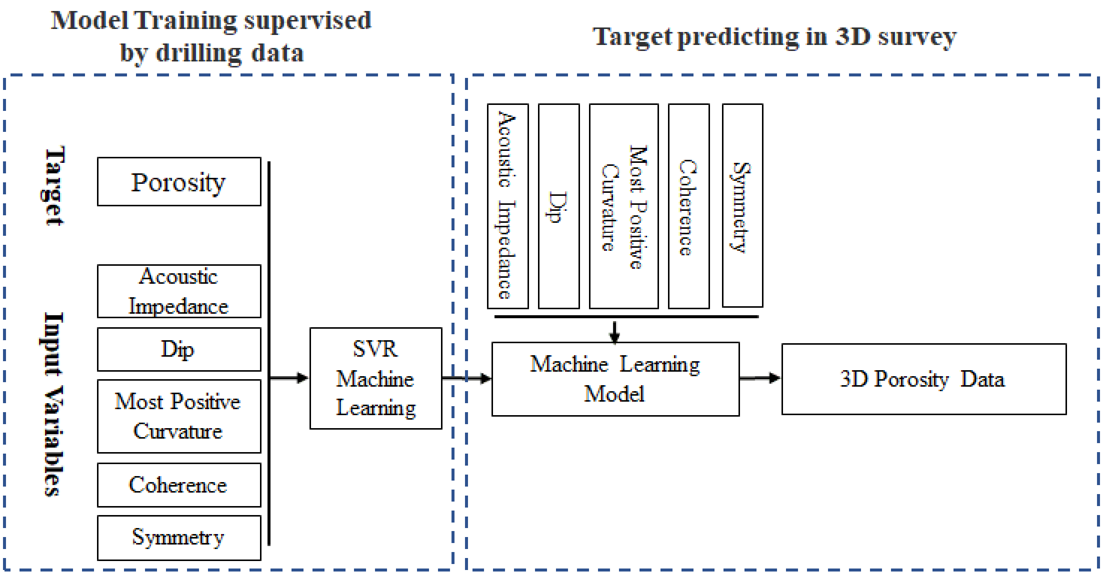

Fig. 10. Support vector machine predicting reservoir porosity flow chart

Fig. 11 shows the measured porosity curve (red) and the predicted porosity curve (blue) for seven wells in the study area. It can be seen that the prediction results are in good agreement with the measured data. Fig. 12 is a cross-sectional view of the prediction results of porosity. From the perspective of the distribution of porosity, it is similar to the wave impedance, indicating that the porosity is most affected by the wave impedance. However, due to the participation of cracks, the porosity distribution is not completely consistent with the wave impedance.

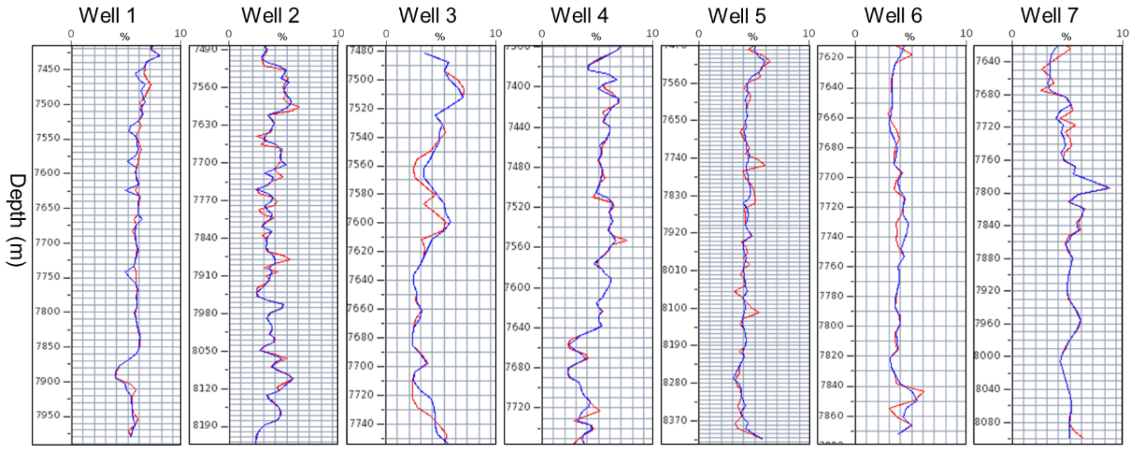

Fig. 11. Support Vector Machine Predicted Porosity (Blue) vs. Measured Porosity (Red)

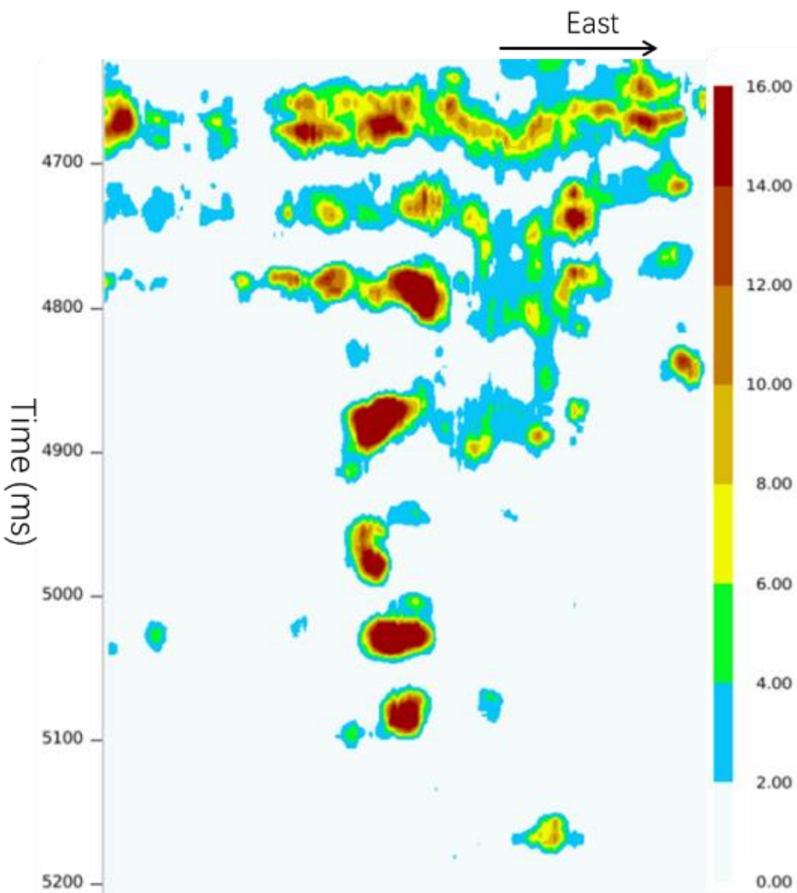

Fig. 12. Study of Porosity Profile

4. Conclusion

The porosity and fracture pore content of carbonate reservoirs jointly control the wave impedance. Therefore, it is necessary to know the wave impedance and the pore content of the crack at the same time to predict the porosity. However, the fracture pore content is usually difficult to obtain, and it is difficult to predict the porosity by a conventional algorithm.

Training the prediction model with the wave impedance to porosity and crack attribute using the support vector machine technology is a data-driven prediction method. Our application shows that this method has achieved some good results in predicting porosity and is also an effective attempt of AI technology in this field of oil and gas exploration.

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