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Researches on Qualitative Recognition of Flushed Zone in Q Block on Deep Forest

Rui Su

College of Geosciences, Northeast Petroleum University, Daqing Heilongjiang 163318, China

Abstract. In this paper we propose a method on qualitative recognition of flushed zone. We extract the morphometric parameters of logging curves to better reflect the change relations. We use deep forest model which learns the representation layer by layer. The model is more robust and have a higher accuracy than other model. This method has an excellent application performance in Q block.

Keywords: Morphometric parameters, deep forest.

1. Introduction

Offshore Q block in P oil field is a Fault control anticline structure sandstone reservoir with certain natural water body energy. Put in production in May 2006, produce oil by natural formation pressure. After several decades of development, the gas field have entered into the middle or last period of development. To maintain the good yield, convert to water-flood to retain the initial formation pressure in September 2008, it finally get into the high water period in 2013.In recent years, plugging strategy is an important measure to stabilize production and control water cut. Along with water flooded extent increase, the ratio of flushed zone in reservoir increased sharply. Effect on production efficiency by water plugging low more. Therefore, integrated interpretation and research of various logging data to the flushed zone of Q block, has great importance to clarify water-flooded layer status and keep stable production and improve oil recovery. The sandstone reservoirs of M strata and N strata are main production horizon of Q block. Rock physical property analyze indicates that the porosity of the sandstone reservoirs is mainly distributed in the 20%-40%. And the permeability is mainly distributed in the 0.1-20.0μm2. Belongs to the medium-high porosity, medium-high permeability reservoir. The pattern is rejection of produced water. The salinity of injection water is similar to the salinity of stratum-water, which makes it no obvious change to that before flush. The range of distribution of shale content in Q block is wide, which causes the similar characteristic that both high mud bearing reservoir and flushed zone shows low resistivity value and the difference between dual and shallow lateral logging. This is very difficult to distinguish and cause difficulties in qualitative identification of flushed zone. The morphometric parameter of logging curves can reflect the difference of shape between logging curves. Only by the morphometric parameter of logging curves can not distinguish argillaceous and flushed zone. Deep forest is a kind of deep nonlinear model. It has a great ability of classification on qualitative identification of water flooded layers and zones. Therefore, the author propose a kind of morphometric parameter extraction method which concerns shale content. Combines deep forest, proposes a more efficient way to qualitatively identify water flooded layers and zones to solve the difficult classification problem. Finally, we handle the test logging data and evaluate the actual effect of this method.

2. Morphometric parameters of logging curves

A morphometric parameter is an important kind of parameter which effectively describe the relationship among forms of logging curve[1]. It has higher computing power and stronger mode identification and classification ability. It can describe the correspondence between porosity logging curves and resistivity logging curves more clearly. Morphometric parameters have been widely used in fluid property identification. The common parameters are relative center of gravity, elliptic degree and plumpness coefficient.

Figure 1 describe some parameters about the definition of morphometric parameters:

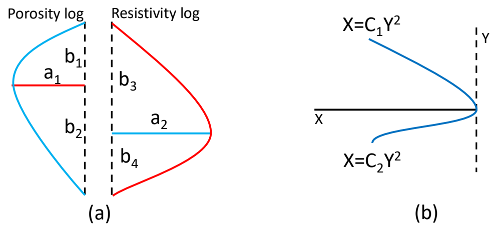

Figure 1. The definition of elliptic degree and plumpness coefficient

The mathematical expression of morphometric parameters of logging curves is shown as follow:

1 relative center of gravity

$$\mathrm{Gr} = b_1/(b_1 + b_2)$$

2 elliptic degree

$$\mathrm{Ep} = (b_1 - b_2)/a_1$$
$$\mathrm{Er} = (b_3 - b_4)/a_2$$

3 plumpness coefficient

$$\mathrm{Pc} = C_2/C_1$$

In the process of waste water reinjection, vertically, the permeability in sandstone reservoir will change with the sedimentary rhythm. In the process of moving along of injected water in the reservoir. The injected water will usually be pushed forward priority along reservoirs with high permeability. As a result, the sedimentary rhythm of reservoir directly influence the position of water in reservoir. Under different hydrodynamic conditions, the reservoir types can be classified into 4 types as homogeneous rhythm, positive rhythm, reverse rhythm and compound rhythm. Reservoir with different sedimentary rhythms have different waterlogged characteristics. This feature usually can be reflected by contrasting the corresponding relation between porosity logging curves and resistivity logging curves.

Deep Forest

Deep forest is a kind of advanced ensemble decision tree classifier[2]. Its ability is better than common machine learning model. Meanwhile, contrast to deep neural network, deep forest has a very good performance in most machine learning task. Deep forest is easy to train. Moreover, the data set of qualitative identification of water-flooded layer is usually small. When we use deep neural network to solve problem on small data set, overfitting usually occurs. However, deep forest can solve the problem caused by the scale of data set.

In deep neural network, represent learn usually depends on the processing of original feature by layers. Inspired by this, deep forest uses a cascade structure. As shown in figure 2, each layer transmits information through previous layers. And output result to the next layer.

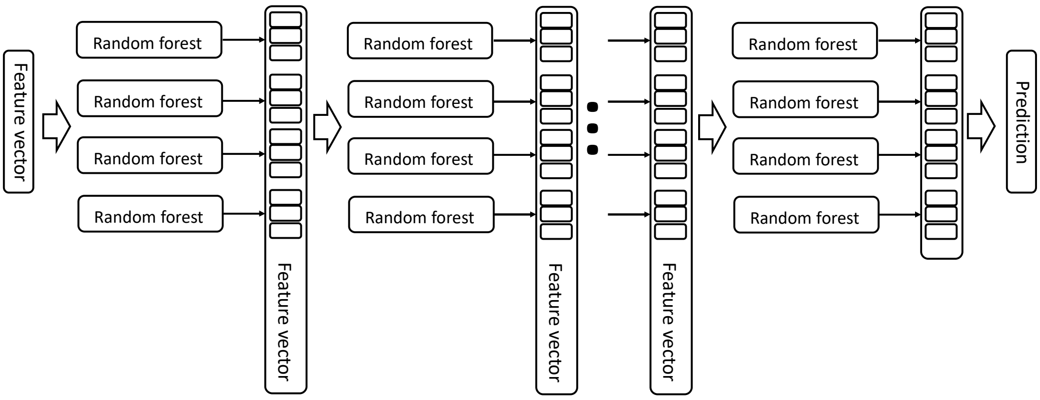

Figure 2. A cascade structure in deep forest

Each layer is an ensemble of random forest. Diversity is the key of ensemble structure. So we import many kind of forests to enhance diversity. In this paper, the author use entirely random forest and random forest. Each entirely random forest has 300 trees as basement. And the number increases in order of 10 entirely random decision trees. Entirely decision tree select a feature as the split of node randomly. Each random forest has 300trees as basement. And the number increases in order of 10 decision trees. Select the biggest gini index as the split node. The distribution of estimated classes form a class vector. The class vector connect the original feature as the input of next layer.

To decrease the risk of overfitting, the class vector generated by each forest is gotten by k-fold cross validation. Concretely, each sample will be trained for k-1 time. And generate k-1 class vectors. These class vectors are averaged into the final class vector as input to next layer. After extend a new layer, the representation will be estimated by validation set. And the training will be stopped when the representation do not remarkable increase. Therefore, the number of cascade layer is obtained automatically.

The input vector include 18 original features. There are no add multi-grained scanning operation because the number of feature is not much. The sample quantity is 1175. These sample will be used to train an entirely random forest and a random forest, which include 300 decision trees. Finally, the length of output vector is 3 including oil, flushed and water.

Table 1. Summary of hyper-parameters.

Deep forest	Parameters
Base model	Entirely random forest, random forest
Number of forest in each layer	20
Number of layer	10
Trees in each forest	200
Max deep	20

The flush dataset includes oil, flush and water, each represented by 18 logging curve features which contain both the curve value and morphometric parameters. We use four different models in solving this problem. The best accuracy is cultivated by deep forest.

Table 2. Comparison of test accuracy on flush dataset

Deep Forest	97.56%
Random Forest	94.20%
Logistic Regression	92.68%
Adaboost	89.56%

3. Conclusion

In this paper we extract morphometric parameters of logging curves which can reflect the relationship among the variation of different curves. Deep forest can have a robust and excellent performance on qualitative recognition of flushed zone. It enhances the representation layer by layer. Finally, this method gets a very good result.

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