Application of Evolutionary Neural Networks for Well-logging Recognition in Petroleum Reservoir

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Abstract - A critical task of well-logging interpretation is to differentiate oil-gas-water layers. Other approaches based on data exploration and low recognition rate are difficult to generalize oil-gas-water layers identification because of the high moisture content in the later period of development. In this research we utilize evolutionary neural networks to build the interpreting model of oil-gas-water layers and extracting well-logging parameters. By using an evolutionary neural network method to recognize reservoir stratum, it can efficiently distinguish oil-gas-water layers.

Keywords - genetic algorithms; neural network; evolutionary neural networks; oil-gas-water layer recognition

I. INTRODUCTION

The recognition accuracy of oil-gas-water layer is not only the key link in improving the efficiency of exploration, but also offers critical basic data for the disposition and planning of development. In the late-mid period of water-injection development in oil fields, the moisture content of production in oil wells is significantly higher; it will heavily affect oil production as well as data exploration. Therefore, it is necessary to know the exact situation of the underground oil-gas-water layer [1][2]. Furthermore, although the matching rate of the oil-gas layer is relatively high when conducted through manual work, it mainly depends on the rich experience of the well-logging interpretation engineers. Moreover, some other approaches have been proposed to interpret the oil-gas-water layer. However, these approaches do not match the same standards in either accuracy or applicability.

In this paper, we exploit evolutionary neural network pattern classification and function approximation methods [4] in order to distinguish the aspects of the oil-gas-water layers and handle some other methods where it may be difficult to manage data. We can analyze, calculate, and extract various kinds of parameters of the reservoir stratum from the provided oil-gas-water layer data. Then, we can determine various characteristic parameters by using the evolutionary neural network. This is the key link in improving the efficiency of exploration with respect to recognizing the oil-gas-water layers. Evolutionary neural networks build a good foundation for future research and application. Because of our research needs, we chose Daqing oil field [5] as our research setting.

The rest of the paper is organized as follows. In Section 2, we describe previous work on evolutionary neural network and its application, as well as oil-gas-water layers recognition. Section 3 gives an overview of our design. In section 4, we analyze the response characteristic of well-logging. We present our solution to assist oil-gas-water layers recognition in Section 5. Finally, we summarize our contributions and future directions in Section 6.

II. RELATED WORK

At present the primary methods utilized in oil fields are the qualitative interpretation method [6] and the cross plot method [7]. The defect of these approaches could stem from human factors, automation, as well as a low systematic level. With respect to these shortcomings, the forecasting and evaluation of reservoir based on artificial neural networks has evolved into a wide range of methods in research and application. The neural network has strong adaptive learning ability; it can simulate the structure of the human brain and realize its discriminated process through the perception and understanding of things outside.

Although artificial neural networks based on pattern recognition technique have been widely awarded and explored, its application is still in the preliminary stage. Artificial neural networking has irreplaceable functionality compared with traditional statistical methods and can be applied to solve various kinds of non-linear problems. This opens a broader world for neural networks on oil exploration and many aspects of application development. With continuous improvement on the discipline of neural network, the problem turns into one of various subfield sciences of petroleum science.
O.Tapias [8] presents data analysis steps using artificial intelligent techniques including problem exploration, space analysis, surveying data source, data preparation, and building appropriate data mining models. We have a similar research field and research data with petroleum engineering. Furthermore, our research also concentrates on data analysis and processing. We can refer to these analysis procedures so as to excavate and optimize our own data analysis and processing procedures.

William W. Weiss [9] illustrates how to apply artificial intelligence technology into petroleum engineering and introduces certain basic knowledge of both fields, which could help us obtain an elementary and critical comprehension for the combination of these two fields. Fatai Anifowose [10] utilizes the capabilities of data mining and computational intelligence to predict two critical petroleum reservoir characteristics, porosity and permeability by means of hybridization. In our research, we exploit evolutionary neural networks to analyze and test the reservoir data. We and Anifowose both adopt functional approximation methods to train the neural networks, which can help us develop a further understanding for training methods.

III. System Overview

This system is utilized for oil-gas-water recognition. It is also an implementation of the NEAT (NeuroEvolution for Augmenting Topologies) algorithm [13] [14] by using Java language. The idea of the algorithm idea in this system is based on NEAT, and we modify the algorithm and the parameters of original algorithm to satisfy our specific application. Then, we design and develop the application program which suits our research field. Figure 1 shows the system interface as following:

![System Interface Design](image)

**Figure 1. An Example of the System Interface Design**

This system implements the parameters adjusting for neural network, neural network evolving, and oil-gas-water layers identifying.

A. Algorithm and Implementation

NEAT efficiently evolves network topologies and weights by means of three principles. The first principle is protecting innovation, which is mainly implemented through the distance $\delta$ between two network encodings and explicit fitness sharing. Distance $\delta$ is exploited to determine the history which is shared among distinct genomes, to divide the population into species. The distance $\delta$ can be calculated by formula (1).

$$\delta = \frac{c1E}{N} + \frac{c2D}{N} + c3\bar{W} \quad (1)$$

In the formula, E is the number of excess, D is disjoint genes, W is the average weight differences of matching genes, and coefficients c1, c2 and c3 are used to adjust the E, D, and W. The explicit fitness sharing is employed to avoid any one species taking over the entire population. The fitness $f'_i$ can be computed with formula (2) as shown:

$$f'_i = \frac{f_i}{\sum f_j sh(\delta(i, j))} \quad (2)$$

Both the distance $\delta$ and explicit fitness sharing combined together can protect innovation. The second principle is homology, which can be presented by figure 2.

Figure 2 illustrates optimal weights of connections and network structure algorithm. The number beside each node is the node after transformation. The numbers after transformation are labeled as past record. They are used to identify primordial ancestors of each node. New nodes will be given an incremental number. During the process of adding a connection, a single new connected node will be added to the end of the genome, and assigned the next available transformed number. During the process of adding a node, the disjoined connected node will be invisible, and two new connected nodes will be added to the end of the genome. This new node will be located between two new nodes. Another new node that substitutes for this node will also be placed into the genome [12].

![Algorithm Illustrations](image)

**Figure 2. Algorithm Illustrations for Optimize Weights of Connections and Network Structure**
The last principle is that search should start in as small a space as possible and expand gradually. Normally, NEAT will evolve with a population of minimal structures. Structural mutations will augment new connections and nodes into existing networks, resulting in incremental growth. Topological innovations, to a certain extent, can achieve their potential. The structures being optimized will be the minimum necessary to tackle the issue, because the only useful structural additions will survive over a long period of time.

IV. SELECTION AND INTERPRETATION OF CHARACTERISTIC LOGGING CURVE

In well-logging interpretation, the authenticity, representativeness, and generalization of the learning sample are the key to determine predictive results. It is mainly composed by the lithology analysis data or formation testing result with a set of corresponding logging response values.

Facing a series of sample data, the reasonable trade-off is how to add data due to insufficient sample data is also difficult to determine. Selecting inappropriate data will cause inaccurate forecasting or failure of the network training. Therefore, the selection of logging curve for oil-gas-water layers recognition is a critical job which aims to use evolutionary neural network pattern identification technique to implement automatic computer identification. According to the above complex circumstance, facing large amounts of unknown data to be predicted, we need to ensure the validity and simplicity of the network. Therefore, it is necessary to select sensitive data for reservoir identification from actual analysis of the geology, seism, drilling, well-logging, and testing given data as a learning sample. Sample data consists of various kinds of possible situations from forecast data, thus improving the predictive ability of the network.

By analyzing and comparing with interpretation experience of oil-water layer experts, coring wells related data, and some important theoretical knowledge, repeated testing allows us to discover several logging curves that are very closely related to the reservoir. They are spontaneous potential curve (SP), High resolution acoustic curves (AC), natural gamma ray curve (GR), micro-normal (RMG), micro-inverse (RMN) difference, deep investigate double lateral resistivity log (RLLD), and shallow investigate double lateral resistivity log (RLLS) respectively (REF. Table 1). Therefore, we choose these curves as input characteristic curve of oil-gas-water layer recognition network. We will mainly explain three major important characteristic logging curves for Daqing oil field below.

V. OIL-GAS-WATER LAYER RECOGNITION TESTING

A. Data preprocessing

Before training our system, all data will be preprocessed. There are two purposes of this step:

1) To make all kinds of information normalized, dimensionless, balanced or equal weight, in order to eliminate all unreasonable phenomena.

2) Due to different logging curves having distinct scales, when multiple well-logging curves are zoned automatically, it is necessary to map the logging curves into the range of [0, 1], in order to eliminate the influence of the different scales. The common data normalization processing formula that we used is:

\[ x_n = \frac{x_i}{\sum x_i} \quad (3) \]

\( x_i \) is the corresponding logging value of a certain depth of logging curve No.\( i \). \( x_n \) represents the normalized values of the curve in that depth. After the data is initialized, the next step is network initialization.

B. Build and Initialize Evolutionary Neural Network Model

A three layer BP network model [11] can be divided into any complex plane. Therefore, we built a three layer BP network. The input layer has five nodes, the hidden layer is uncertain, and the output layer has four nodes that represent the hydrocarbon reservoir, oil-water layer, aqueous layer, and dry layer, respectively.

The system uses some parameters to set the neural network initialization. There are two tasks needed to be done:

1) Chose the number of nodes in the neural network.

2) Determine neurons weights, \( W \). There is no explicit approach for determining the number of network neurons. Therefore, we apply weights of connections and network structure optimization methods together to determine the \( W \).

C. Sample Data Recognition

<table>
<thead>
<tr>
<th>RLLD</th>
<th>RLLS</th>
<th>AC</th>
<th>RMG</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.005380</td>
<td>0.006756</td>
<td>0.765317</td>
<td>0.004347</td>
</tr>
<tr>
<td>0.010295</td>
<td>0.009144</td>
<td>0.660143</td>
<td>0.011464</td>
</tr>
<tr>
<td>0.015641</td>
<td>0.015705</td>
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<td>0.01728</td>
</tr>
<tr>
<td>0.029719</td>
<td>0.029478</td>
<td>0.746325</td>
<td>0.031926</td>
</tr>
<tr>
<td>0.043226</td>
<td>0.035631</td>
<td>0.953898</td>
<td>0.021517</td>
</tr>
</tbody>
</table>

Table 1. Sample Logging Data from Daqing Oilfield - Give Category (GC), Testing Result (TR)

The data of the characteristic value of the curve is provided by Daqing Oilfield. Real categories include oil, gas, and water layers categories, which are divided into three classes. Category numbers are used to verify the test
results. If they are the same, then indicate success; otherwise, indicate failure. To identify the division of the category see Table 2. We adopt the Daqing Oilfield south 7-20-Index 654 core well as key well in order to accurately set up the oil-gas-water layers prediction model. Split the layers automatically for the key well, and compare the logging value with the result data. We select 18 samples as prediction data (See Table 1), and choose 102 samples as network training samples, with a total of 120 sample data.

This system aims to identify the oil-gas-water layer; therefore, the classification could be divided into three categories. The system exploits function approximation models of evolutionary neural network as the principle means of classification. Thus, we need to generate three function approximation values initially, and then determine testing results by comparing the tested data with these three function approximation values. Table 1 contains three kinds of function approximation value ranges created by the training of evolutionary neural network.

<table>
<thead>
<tr>
<th>Category</th>
<th>Approximation Value Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;=0.5</td>
</tr>
<tr>
<td>2</td>
<td>0.5-0.7</td>
</tr>
<tr>
<td>3</td>
<td>&gt;=0.7</td>
</tr>
</tbody>
</table>

Table 2. Three Kinds of Function Approximation Value Ranges

D. Data Training Result

After training, the prediction samples could be tested. The results are the approximation value corresponding to each row of the sample data (see Table 1). We can use the approximation value to categorize according to Table 2.

Finally, we can classify the test data through comparison with the function approximation values ranges (Classification results could be seen in Table 1).

During the sample identification, some data is hard to be identified, because the data is often mixed with oil-water layer data. The existing description method is quite effective, so other indicators are necessary to promote the classification for oil-gas-water layers. Therefore, when describing the actual reservoir data, we need to analyze the exact actual issues and combine the various classification approaches. By doing so, we are able to obtain more accurate judgment and classification.

Evolutionary neural network works as an excellent classifier [3] [4]. After initial learning, the network structure could be confirmed, and it could be utilized to recognize new unknown data without any modulation. However, the network should not be fixed due to alterations of data nature with the actual situation. The network should be gradually corrected under the condition of more and more sample data and take advantage of the existing network mode. This will function as the initial nodes to train new sample data, which could generate the new network structure. This is fairly useful for solving practical problems.

VI. CONCLUSION AND FUTURE WORK

The paper researched evolutionary neural network and how to use it to describe the reservoir description and apply it to the field of oil-gas-water layer recognition. We used the function approximation method of evolutionary neural networking in the model based on amounts of well-logging parameters, to do the cluster analysis of lithological characters. We can make more accurate decisions by combining the actual situation and cluster results. The reservoir description can be achieved through this method. By looking at the comparative analysis of well-logging interpretation results, we find the average accuracy rate of parameter classification by using the evolutionary neural network model can reach 88.89% or higher.

However, this method has its limitations. For instance, when the number of network connections are too great and there are a large number of nodes, the calculated amount will be too large, which requires a longer time to learn. Additionally, the selection of initial network weights has a significant effect on the network astringency. Also, due to the complexity of geographic condition, the current data used to describe the reservoir distribution is insufficient, thus making network learning outcome less ideal. Therefore, determining how to use other indices to describe the distribution is the main task of the next step.

In addition, the pre-processing of data is worth studying as well. We found that the data will always be influenced by noise, which yields unsatisfactory network learning outcomes. Although the evolutionary neural network has certain fault-tolerant capability, it is still difficult to obtain more accurate sample data.

To the evolutionary neural network itself, it has many issues worth researching, such as how to set the initial parameter of the network and network size to generate an optimal network learning effect.

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