A FUZZY APPROACH FOR POROSITY CLASSIFICATION BY USING WELL LOG DATA

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ABSTRACT *Intelligent computing approaches are recently utilized for interpretation tasks in well-logging. This is mainly because of the necessity of processing well logs where no complete data containing e.g. core data are available. In this case, we use fuzzy logic for classifying the porosity types by using the well log data of the studied field located in the Iranian offshore of Persian Gulf. The classification of porosity types was based on known classification of log data belonged to wells no.1 and no.2 into primary, cavernous and micro-fractures porosity classes. Each fuzzy class was regarded as a union of several fuzzy granules that each granule was also obtained by the intersection of correspondent membership functions. The analysis of the achieved results reveal that the fuzzy logic approach we developed can compensate for the absence of exact information with maintaining accuracy of data analysis and decreasing costs at the same time.*

INTRODUCTION

In petroleum reservoir characterization it is classically exploited the statistical and/or physical approaches. The statistical approaches are more useful only when a priori information regarding nonlinear input-output mapping is available. In physical approaches, the need to mathematical modeling and consequently imposing the several assumptions for simplification or adding extra formulating for the description of phenomena, makes the problems complex and sometimes unrealistic and inaccurate. Several log interpretation techniques by these approaches are developed (Huenges et al., 1997; Doveton, 2000; Verga and Viberti, 2002). Nevertheless, risk and uncertainty assessment using intelligent computing approaches have recently become the main issues in petroleum reservoir characterization and improved oil recovery (Wong and Nikravesh, 2001; Aminzadeh and Wilkinson, 2004). Different types of artificial neural networks have been used for reservoir characterization and also for well log interpretation (Pezeshk et al., 1996).

Porosity as a fundamental rock characteristic has a significant effect on petroleum field operations and petroleum reservoir management. In un-cored intervals and wells, the reservoir description and characterization approaches using well logs represent a significant technical as well as economic advantage. We use several well log data in the study for the task of porosity classification. The approach of description of porosity classes by fuzzy classes includes several fuzzy granules to be applied. Such a granulation of classes makes it possible to describe the intersected porosity classes in the space of considered attributes.

THEORY and METHOD

The integration of acoustic and electrical well log data was proposed for the quantitative estimation of the secondary porosity in carbonate formations (Brie et al., 1985). In the approach, a homogeneous host rock is presented as a double porosity formation that contains spherical secondary pores. Unfortunately, the assumption of the secondary pore to be in the form of spheres does not permit to exploit this approach for fractured formations.

In a recent technique of the secondary porosity estimation by acoustic core and well log data, the elastic moduli of the double porosity medium are considered as functions of both primary and secondary porosities (Kazatchenko et al. 2003). Unfortunately, the measurements of S-wave velocity needed for this approach are not always available that is why in this paper, another classification approach is developed.

We seek the description of porosity classes C_1 (cavernous porosity), C_2 (primary porosity), C_3 (micro-fractures porosity) by fuzzy classes G_1, G_2 and G_3. The porosity classification was based on known classification of log data of well no.1 on three porosity classes C_1, C_2 and C_3. This well log data were used as a training data while the log data from well no.2 with the known classification on porosity classes C_1, C_2 and C_3 were used as a testing data.

The fuzzy class G_i was regarded as a union of three fuzzy granules: $G_i = G_{i1} \cup G_{i2} \cup G_{i3}$. The fuzzy granules G_{ij} were also obtained by the intersection of correspondent membership functions MF_{ijk} defined on the domains of parameters p_k. We used the generalized Gaussian combination membership function. The separability value for a point x belonged to class C_i in the training data set was calculated as follows:

$$Q(x) = MF_i(x) - \max(MF_k(x), MF_j(x)) \tag{1}$$

criterion of classification was equal to $Q_s = Q_1 + Q_2 + Q_3$. The maximization of this criterion was utilized to find optimal parameters of membership values.

The optimization algorithm of constraint nonlinear minimization from MATLAB Optimization Toolbox was applied that searches the minimum of a given function. Thus, we utilized $F = -Q_s$ for optimization.

For the training data set, 80% of points from each class were randomly selected. Other points were utilized in the testing data set. Finally, fuzzy rules of the following type were generated based on the obtained granular classification of data:

If (p_1 is MF_{i11} and p_2 is MF_{i12} and p_3 is MF_{i13})

or (p_1 is MF_{i21} and p_2 is MF_{i22} and p_3 is MF_{i23})

or (p_1 is MF_{i31} and p_2 is MF_{i32} and p_3 is MF_{i33})

then data point is C_i (2)

where p_1 is RHOB, p_2 is NPHI and p_3 is GR.

The true classification on the training data set was equal to 75%, 68% and 90% for classes C_1, C_2 and C_3, respectively. This classification on the testing data set was equal to 33%, 62% and 79%, respectively. Unfortunately, an extension of the obtained results on another well was problematic. For this reason, other models based on fuzzy granulation of classes were studied.

First, instead of the average value of separability Q_i of the points for each class C_i, simply the sum of these values was calculated. For fuzzy classes obtained by this new optimization procedure the true classification on the training data set was equal to 81%, 85% and 75%, respectively and on the testing data was 55%, 61% and 76% for porosity classes C_1, C_2 and C_3, respectively.

The analysis of obtained granules composing the fuzzy classes G_1, G_2 and G_3 shows that really only two granules may construct each of these classes because one granule in each fuzzy class contain no points or only few points. Thus, in the next modified model we sought a simpler representation of porosity classes by only two granules $G_i = G_{i1} \cup G_{i2}$. Consequently, the true classification on the training data set was equal to 77%, 80%, and 84%, respectively. The membership functions obtained by optimization procedure for fuzzy class G_3 are shown in **Figure-1**.

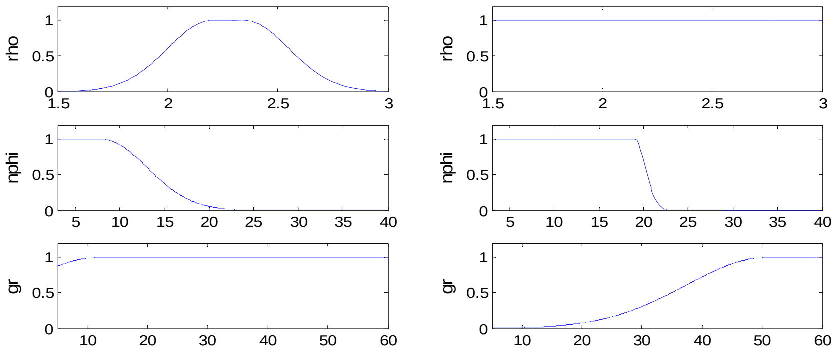

Figure-1. Membership functions defined on the domains of parameters $p_1 - p_3$ for the granules G_{31} (left) and G_{32} (right) of the micro-fractures porosity class G_3.

Testing the obtained classes on the log data from well no.2 gives the true classification of 61%, 56% and 78% for the classes C_1, C_2 and C_3, respectively. These testing results are better than testing results obtained for fuzzy classification based on three granules.

The transfer of fuzzy granules constructed on the training data and the testing log data shows that these log data have different domains for some parameters.

It was supposed that a correction of fuzzy sets obtained on the training data which is preserving the same linguistic interpretation on the domain of the testing data will increase the classification capability of fuzzy solution. Corrected in such a way, the membership function for GR parameter is shown in **Figure-2**.

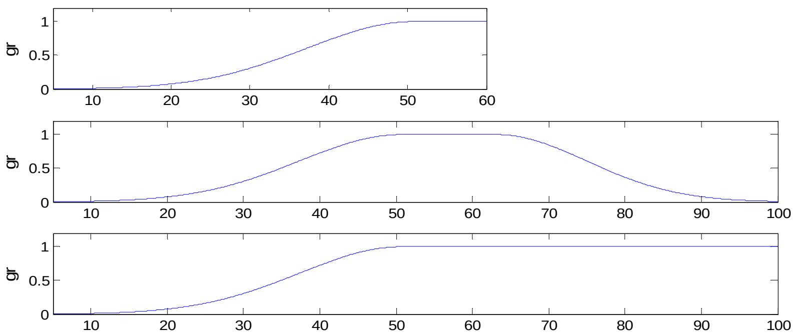

Figure-2. The correction of membership functions for granule G_{32} transferred from the domain of training log data (top) to the domain of testing log data and corrected on this domain (middle) to preserve the same linguistic interpretation as in top (down).

After this correction, the true classification was obtained as 66%, 57% and 81% for the classes C_1, C_2 and C_3, respectively. These testing results are slightly better than results obtained for fuzzy classification with non-corrected fuzzy granules.

The final description of fuzzy classes is given by the rules of the following type:

If (p_1 is MF_{i11} and p_2 is MF_{i12} and p_3 is MF_{i13})

or (p_1 is MF_{i21} and p_2 is MF_{i22} and p_3 is MF_{i23})

then data point is C_i (3)

where p_1 is RHOB, p_2 is NPHI and p_3 is GR.

Fuzzy granules can describe not just crisply separated classes existing in many practical situations. The results obtained by the fuzzy granulation of porosity classes describe a fuzzy nature of these porosity classes in considered set of parameters. The obtained fuzzy classification gives sufficiently good classification of micro-fractures porosity class in carbonate formations, which is the most important porosity class for petroleum reservoir exploration. These rules form the basis for the further classifications of the pore space-based on well logs.

CONCLUSIONS

This approach needs no previous assumptions to build a model from the measured data set. As a pattern recognition technique, it clearly requires a good data set to be valid and representative of different features existing in the petroleum reservoir under study.

In porosity classification problem there are usually imprecise conditions, some measurements are missing and therefore fuzzy approaches seem to be more suitable than crisp ones. This classification is useful under the conditions of a deficiency of the information, for example during data processing about the old boreholes.

Among the advantages of applying the fuzzy rules for porosity classification is that they allow complementing the future analysis by the rule set constructed in this paper with the lithological descriptions of core samples usually available as qualitative or linguistic statements.

These developed porosity classification models can be exploited to make predictions for the wells from the petroleum reservoirs relating to micro-fractured carbonate formations. This approach can be extended to the rock type characterization in the absence of adequate geological information.

Finally, an interesting application of the approach is the cost reduction through selecting the rational combination of the set of geophysical approaches designed to solve the problems of the production process under several specific geological and technical conditions.

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