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APPLICATION OF ARTIFICIAL NEURAL NETWORK IN GEOLOGY: POROSITY ESTIMATION AND LITHOLOGICAL FACIES CLASSIFICATION

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ABSTRACT

Based on the relationship between porosity (or lithological facies) and other petrophysical properties, Artificial neural networks (ANN) are respectively trained for porosity estimation and lithological facies classification, using core porosity (CPOR) data and core lithological facies interpretation results of part of core interval together with some well logs (petrophysical properties). After the ANN were constructed, they were used for porosity estimation and lithological facies identification in both trained and untrained core intervals, for further analysis of errors or accuracies of the estimated results and ANN. After careful analysis, the error of estimated porosity is from -0.3 to 0.3, and the accuracy of lithological facies identification is 0.7, both showing high reliability of ANN. The constructed ANN can be confidently applied for other un-cored wells or intervals.

INTRODUCTION

Facies classification is carried out by studying the lithological properties of rocks, which are characteristic of modern sediments, accumulating in certain physical and geographical conditions. In this study, a new 1D-CNN model, which is trained on various optimization algorithms, is proposed. The photoelectric effect, gamma ray, resistivity logging, neutron-density porosity difference, average neutron density porosity and geologic constraining variables are considered as input data of the model. Acceptable accuracy and the use of conventional well log data are the main advantages of the proposed intellectual model. The proposed model is compared with a recurrent neural network model, a long short-term memory model, a support vector machine model, and a k-nearest neighbor model and shows more accurate results in comparison with them.

The most popular geophysical research of the well, conducted with the purpose of revealing oil in a geological section, is logging. Well logs are physical and chemical measurements of rocks recorded by lowering specialized sensors into the wells after drilling. It allows determining the porosity, permeability, fluid composition, information about oil and gas saturation, etc. With the help of logging the character of the

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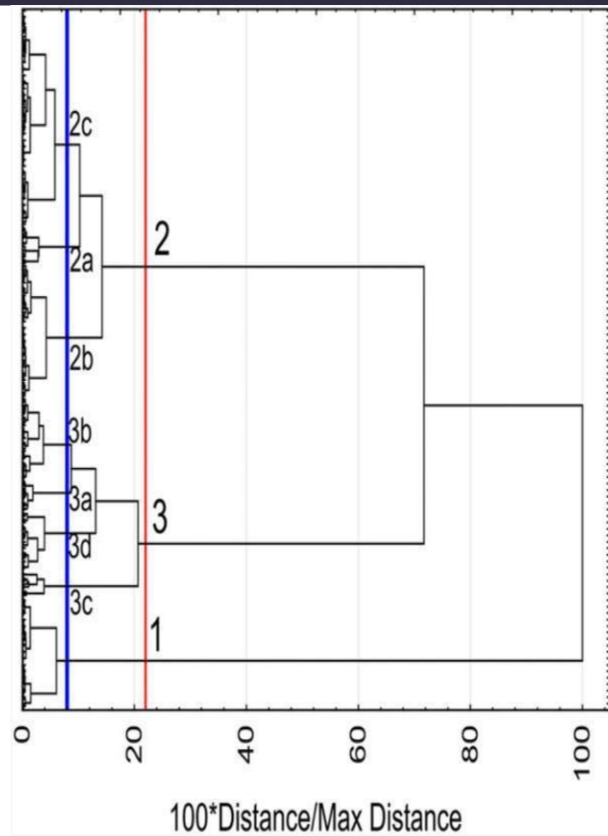
drilled layers is determined without core selection.

The facies (part of the layer that differs from the adjacent layers by lithological composition) contain characteristic features found in the core of reservoir rock samples that were taken from wells. They are the basis for characterizing the reservoir and constructing its model. Experts analyze them to determine the type and sequence of facies. This task is tedious and time-consuming. The process of wells drilling and cores obtaining for well analysis is expensive. These costs increase significantly as the number of wells increases. Therefore, it is necessary to develop approaches for facies determination using well log data.

Most researchers suggest using artificial neural networks (ANN). Neural networks can solve problems that cannot be solved with the help of conventional calculations and discover very complex relationships between several variables. ANN methods have a remarkable ability to establish a complex mapping between nonlinearly coupled input and output data (Nakutnyy et al., 2008). In petroleum engineering, these networks are used when there is not enough data to interpret (Auda and Kamel, 1999) (Ayala and Ertekin, 2005).



Hierarchical clustering dendrogram

ANN is used to estimate all unknown reservoir parameters. The coefficients of interpolating Chebyshev polynomials were considered as input to the ANN (Adibifard et al., 2014). Different training algorithms used to train ANN, and the optimum number of neurons for each algorithm were obtained by minimizing the mean relative error (MRE) over test data. Levenberg-Marquardt algorithm showed the best result.

Methods based on two different types of intelligent approaches, including ANN linked to the particle swarm optimization (PSO) tool, was developed to evaluate the productivity of horizontal oil wells (Ahmadi et al., 2015). The authors of the paper suggest that the presented prognostic model

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can be used for effective forecasting of well productivity, in particular, at the initial stages of the evolvement of horizontal well drilling.

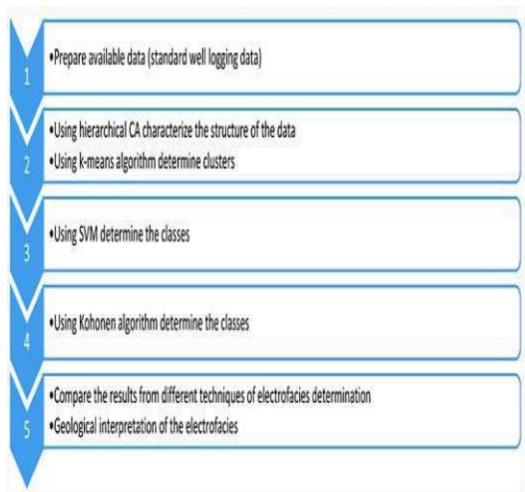
Log data is used for lithological analysis, which is an integral part of facies analysis, taking into account lithological features of rocks (composition, structure, presence of mineral indicators of the environment, etc.) (Serra, 1984). Rocks that have numerous physical and chemical properties can be used in classification.

Self-organizing map neural network (SOM-ANN) and hierarchical cluster analysis (HCA) were utilized to characterize lithofacies in uncored but logged wells (Sfidari et al., 2014). The electrofacies derived from the SOM networks showed a good agreement with reservoir geological (lithofacies) and petrophysical data.

Variations in petrophysicallithofacies were evaluated, and structural facies-controls were identified (Ohl and Raef, 2014). A neural network petrophysicalfacies classification was based on training and validation using three petrophysically-different wells and three volume seismic attributes, including the wavelet of the reservoir-top reflection.

The term electrofacies was introduced by Serra and Abbott in 1980. They defined electrofacies as the set of log responses which characterizes a bed and permits this to be distinguished from others. Based on standard well logging data, like natural gamma ray, bulk density, neutron porosity, resistivity or P-wave velocity log, the electrofacies can be defined and often they correspond to one or more lithofacies. Traditionally lithofacies have been identified manually, based on core description and their correlation to well logs.

The most important step for electrofacies determination is core and log data integration. Electrofacies are based on log responses in the scale according to sampling rate of well logging while facies description based on cores are often in millimeters scale. We have to realize that electrofacies analysis given as general information about rock properties changes and can be used for pattern recognition in geological profiles of wells.



Flowchart of analyses for electrofacies characterization

EXISTING METHOD

The objective of the support vector machine algorithm is to find a hyperplane in an *N*-dimensional space that distinctly classifies the data points. Support vectors are data points that are closer to the hyperplane and influence the position and orientation of the hyperplane. Using these support vectors, we maximize the margin of the classifier. Deleting the support vectors will change the position of the hyperplane. In the SVM algorithm, we are looking to maximize the margin between the data points and the hyperplane. SVM has shown good performance in rock classification tasks (Wong et al.; Sebtosheikh et al.

In this study, we performed two different kernel functions of SVM in the electrofacies prediction:

$$\text{linear: } k(\boldsymbol{x_i}, \boldsymbol{x}) = \boldsymbol{x_i} \cdot \boldsymbol{x}$$

Radial basis (RBF)

$$k(\boldsymbol{x_i}, \boldsymbol{x}) = e^{(-\gamma|\boldsymbol{x_i} - \boldsymbol{x}|^2)}$$

METHODOLOGY

Cluster analysis

Clustering methods have been developed in order to combine objects similarity in terms of studied features into homogeneous groups, called clusters. The members of clusters are at once alike and at the same time unlike members of other groups. In the clustering methods, we distinguish:

- the hierarchical methods that show the entire structure of the data set and allow the user to make a decision regarding the number of clusters, e.g. dendrogram method;

- the non-hierarchical methods, where the number of clusters is determined in advance, and then the objects are assigned to groups based on similarity, e.g. *k-means* method.

In clustering methods, the measure of the similarity of objects is the distance between objects.

In the hierarchical methods, in the first step of analyses, a distance matrix is created (e.g. calculated according to the Euclidean or Manhattan metric). Then the most similar (the nearest) objects are searched and the first cluster is created. In the next step, the distance matrix is reduced and the distances of the objects to the newly created cluster are re-calculated. This process is repeated until all objects are grouped in one cluster.

DATA CONTENTS

As an input data in electrofacies analysis, standard well logging data were taken. Those well logs have been selected which are highly sensitive to lithology, porosity, and water or hydrocarbon saturation.

GR (API)—natural gamma-ray log, total radioactivity of the formation. Gamma-ray log is a first shale indicator. Among the sedimentary rocks, shales have the strongest intensity gamma radiation due to higher concentration of K, U, Th elements. Potassium and thorium tend to be concentrated in clays, whereas uranium often shows high content in source rocks because of adsorption by organic matter.

LLD (ohmm)—deep resistivity log, measured by laterolog tool. Resistivity is the primary physical property that allows

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determining reservoir properties, in particular porosity and water and/or hydrocarbon saturation. When organic matter is present in shales, whether in the form of insoluble kerogen or soluble bitumen, it characteristically increases resistivity.

DTP (μs/ft)—compressional wave slowness log. Principal use of sonic log is porosity evaluation. In shales, lowers sonic velocities are observed because of the presence of organic matter.

NPHI (%)—neutron porosity. NPHI values are expressed in standardized neutron porosity units (p.u.), which are related to hydrogen index, HI—an indication of formation's richness in hydrogen. In geological conditions, hydrogen nuclei are supplied by water and hydrocarbons that are mainly distributed in the pore space, thus NPHI is a good porosity indicator. In shales, NPHI curve has abnormally high values of neutron porosity. This is because clay water consists of free water, clay bound water as well as lattice water, which is part of clay mineral structure. Additionally, organic matter that has characteristic high hydrogen index causes a noticeable increase in NPHI readings in shales and clays.

RHOB (g/cm3)—bulk density log. It is overall rock's density that is a function of matrix density (mineral components forming the rock) and total porosity. Thick series of shales demonstrates progressive increase in density due to the compaction, when formation is overpressured there is a break in normal shale compaction trend manifested by a drop of bulk density, organic shales are distinguished by clear low anomalies on RHOB log because organic matter has much lower density in comparison with non-source shales.

PE (b/e)—photoelectric factor log. PE measurements is an effective tool for matrix identification, because is a function of chemical/mineral composition and is independent from porosity.

CARRIER KEY ASSUMPTION

Artificial neural network

Artificial neural networks proposed by Kohonen (1982) are the most popular model of self-organizing networks.

The Kohonen networks work with the following algorithm:

- At the beginning, we have to select several parameters,
- The *n*-dimensional weight vectors v_1, $v_2 \ldots v_l$ of the *j* computing units (randomly selected),
- An initial radius *r*, a learning constant *a* and a neighbourhood **function α,**
- An input vector *ε* (selected by using the probability distribution over the input space),
- The unit *k* with the maximum excitation and for which the distance between v_l and *ε* is minimal,

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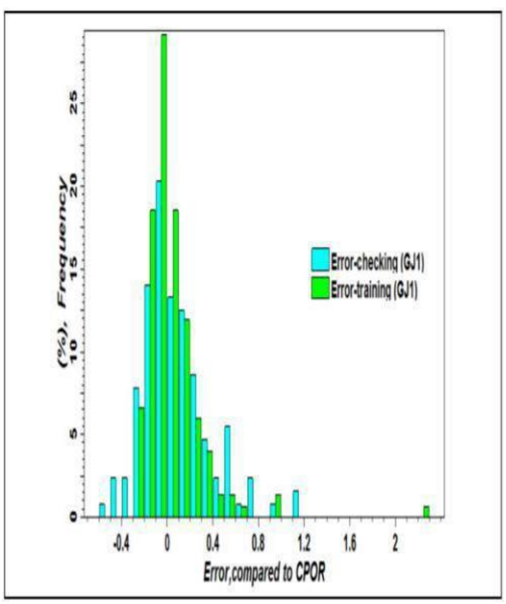
- The weight vectors are updated by using the neighbourhood function

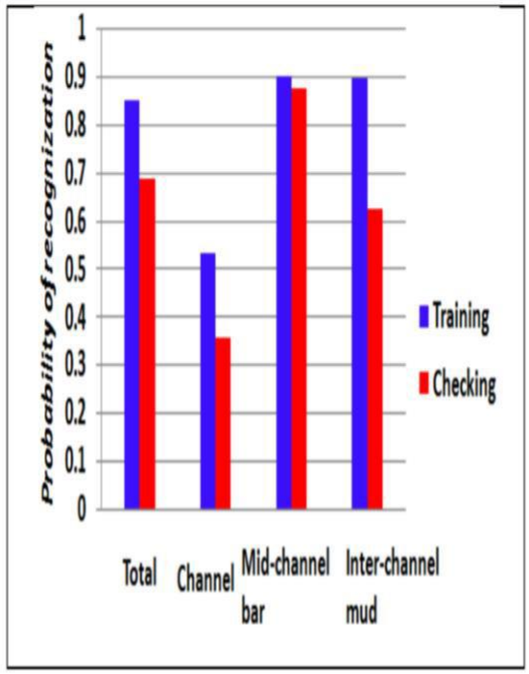
- a and/or α are modified then the recalculation are continued from the beginning (it can be stopped after Z iterations).

By repeating the process several times, arriving at a uniform distribution of weight vectors in input space is expected. During the learning process, both the size of the neighborhood and the value of neighborhood function fall gradually so that the influence of each unit upon its neighbors is reduced. From an initial distribution of random weights, and over Z iterations, the networks settles into a map of stable zones. Each zone is effectively a feature classifier.

RESULT AND DISCUSSION



The histogram of error of estimated porosity compared to CPOR



Probability of recognization of the three lithological facies and total facies for both training interval and checking interval

CONCLUSION

When ANN was used for porosity estimation, the error for untrained interval, varies from -0.3 to 0.3, showing high reliability of ANN, which can be confidently used for other uncored wells or intervals. When it comes to lithological facies

classification, the probability of recognization for total untrained interval is high to 0.7, showing strong classification ability of ANN in lithological facies. But the identification of transitional facies may be less accurate than others, due to

itstransitional characteristics in petrophysical properties. ANN is a cheap, quick, stable and relatively accurate method for porosity estimation and lithological facies classification for reservoirs. However

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it is still not widely used nowadays, and needs more deep researches.

REFERENCES

[1] Doveton J (1994) Geologic log analysis using computer methods. AAPG Computer Applications in Geology, vol 2, Tulsa

[2] Hair JF Jr, Black WC, Babin BJ, Anderson RE, Tatham RL (2006) Multivariate data analysis. Pearson Prentice Hall, New Jersey

[3] Jarzyna JA, Krakowska PI, Puskarczyk E, Wawrzyniak-Guz K, Zych M (2018) Comprehensive interpretation of the laboratory experiments results to construct model of the polish shale gas rocks. In: POL-VIET2017:scientific-research cooperation between Vietnam and Poland: Krakow, Poland, November 20–22, 2017; E3S Web of conferences, vol 35, art. no. 03009, pp 1–8. ISSN 2267-1242

[4] Kohonen T (1982) BiolCybern 43:1 CrossRef

[5] Sibson, R, "SLINK: an optimally efficient algorithm for the single-link cluster method," The Computer Journal (British Computer Society). 16 (1): 30–34.

[6] Defays, D., "An efficient algorithm for a complete link method," The Computer Journal (British Computer Society) 20 (4): 364–366.

[7] Lloyd, S., "Least squares quantization in PCM," IEEE Transactions on Information Theory 28 (2): 129–137.

[8] Ester, Martin; Kriegel, Hans-Peter; Sander, Jörg; Xu, Xiaowei, "A density-based algorithm for discovering clusters in large spatial databases with noise," In Simoudis, Evangelos; Han, Jiawei; Fayyad, Usama M. Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD-96). AAAI Press. pp. 226–231.

[9] Achtert, E.; Böhm, C.; Kröger, P., "DeLi-Clu: Boosting Robustness, Completeness, Usability, and Efficiency of Hierarchical Clustering by a Closest Pair Ranking," LNCS: Advances in Knowledge Discovery and Data Mining. Lecture Notes in Computer Science 3918: 119–128.

[10] R. Ng and J. Han, "Efficient and effective clustering method for spatial data mining," In: Proceedings of the 20th VLDB Conference, pages 144-155, Santiago, Chile, 1994.

[11] Sculley, D., "Web-scale k-means clustering," Proc. 19th WWW.

[12] Huang, Z., "Extensions to the k-means algorithm for clustering large data sets with categorical values," Data Mining and Knowledge Discovery 2: 283–304.