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Automated Prediction of Geometrical, Zone, and Petrophysical Parameters for a Gas-Bearing Reservoir

M. ABDELRAHMAN[1,2], R. Valadez[1], N. Szabo[1]

[1] University of Miskolc; [2] Ain Shams University

Summary

Insightful data on a variety of factors, such as geometrical properties and storage capacity, were obtained through borehole geophysics, which is crucial for assessing the subsurface reservoirs close to the drilling well. The optimization of reservoir exploration, however, depends on the accurate assessment of these characteristics. Additionally, because they are time-consuming and vulnerable to biases in interpretation, classic sequential interpretation procedures of well-logging data are used today. Borehole geophysical datasets from artificial and actual field boreholes were used to test the suggested procedure. In order to verify and validate the prediction of various lithological units and their petrophysical properties in the presence of 5% Gaussian noise, a synthetic dataset was employed. The procedure was further expanded to incorporate other zone factors, including shale parameters and Archie's coefficients. The gas-bearing reservoir in Egypt is a suitable case study to evaluate and validate the suggested workflow in a challenging, deep reservoir with significant variability. To introduce several lithological units with various petrophysical and zone characteristics, our automated procedure recorded the interaction patterns and hidden linkages.

Automated Prediction of Geometrical, Zone, and Petrophysical Parameters for Tight Gas Reservoirs.

Introduction

Borehole geophysics is important for evaluating the subsurface reservoirs surrounding the drilling well because it gave rise to insightful information on several parameters including geometrical characteristics and storage capacity (Doveton, 2001). However, Accurate estimation of these parameters is vital for reservoir exploration optimization (Dobróka & Szabó, 2011). Furthermore, the traditional sequential interpretation techniques of well-logging data are time-consuming and subject to interpretation biases. Nowadays, the field of borehole geophysics has seen a revolution concerning the use of machine-learning approaches (Lima et al., 2020). This research focuses on the integration between a robust unsupervised machine learning technique, which is called Most Frequent Value based clustering (MFV-cluster), and borehole inversion to present a fully automated methodology for the prediction of geometrical, zone, and petrophysical (volumetric) parameters. This approach improves the robustness of the inversion process by identifying the different lithological units using MFV clustering and making that prior information guides the inversion process, enabling more focused and accurate parameter estimation within each identified cluster. The use of both techniques can improve the overall understanding of the subsurface in a simultaneous way. The use of MFV-cluster instead of the conventional cluster is essential for overcoming the dependency of initial location of centroids, and decrease the method's sensitivity to outliers (Szabó et al., 2021).

The proposed workflow was tested using synthetic and real field borehole geophysical datasets. The synthetic dataset was used to test and validate the prediction of different lithological units as well as their petrophysical parameters in the presence of 5% Gaussian noise. Furthermore, the workflow was extended to include different zone parameters such as shale parameters and Archie's coefficients. The gas-bearing reservoir from Egypt is an appropriate case study to test and validate the proposed workflow in a complex and deep reservoir with high heterogeneity percentage. This automated workflow captured the interactive patterns and hidden relationships to introduce different lithological units with different petrophysical and zone parameters.

MFV-based clustering

The coordinates of the layer boundaries can be detected using the MFV-cluster method. Steiner (1991) introduced a robust algorithm for locating the most frequent value that is not affected but the outliers. The MFV cluster is based on the weighting of the data, where the weights can be calculated as follow:

$$w_k = \frac{\varepsilon^2}{\varepsilon^2 + e_k^2} \tag{1}$$

where ε is the dihesion. The most frequent value (M) is calculated as the weighted average of x_k elements, where the w_k symmetric weighting function is calculated with the deviation e_k=(x_k-M). Therefore, the algorithm starts to calculate the initial adhesion value from the range of the dataset. In the following iterations, both ε and M will be calculated from each other by using the following equations:

$$\varepsilon_{j+1} = 3 \sum_{i=1}^{n} \frac{\left(x_i - M_{n,j}\right)^2}{\left[\varepsilon_j^2 + \left(x_i - M_{n,j}\right)^2\right]^2} \Big/ \sum_{i=1}^{n} \frac{1}{\left[\varepsilon_j^2 + \left(x_i - M_{n,j}\right)^2\right]^2} \tag{2}$$

$$M_{n,j+1} = \sum_{i=1}^{n} \frac{{\varepsilon_{j+1}}^2}{\left[{\varepsilon_{j+1}}^2 + \left(x_i - M_{n,j}\right)^2\right]} . x_i \Big/ \sum_{i=1}^{n} \frac{{\varepsilon_{j+1}}^2}{\left[{\varepsilon_{j+1}}^2 + \left(x_i - M_{n,j}\right)^2\right]} \tag{3}$$

The implementation of the Steiner weights in the *K-means* clustering, introduced a new robust weighted distance called Steiner distance, while the location of the new centroid can be determined as follow:

$$C_i{}^{st} = \left[\frac{1}{\sum_{q=1}^{M_i} w_q{}^{st}} \sum_{k=1}^{Mi} w_k{}^{st} x_k^{(i)}\right]^{1/2}. \quad (4)$$

Inversion of well logs

For the calculation of layers coordinates and zone parameters, the depth-dependent inversion, which can be called interval inversion, can be used advantageously because of its high overdetermined ratio (Szabó & Dobróka, 2020). The forward problem expresses a nonlinear connection between the well-log data and the model parameters (petrophysical (**m**), zone (**O**), and depth coordinate of the q-th layer (z_q)). Mathematically, the relationship can be expressed as follows:

$$\mathbf{d} = \mathbf{g}(\mathbf{m}, \mathbf{O}, z). \quad (5)$$

The layer thickness can be expressed as a combination of two Heaviside basis functions as follows:

$$L = [u(z - Z_{q-1}) - u(z - Z_q)] \quad (6)$$

where Z_q is the depth coordinate of the q[th] layer. The nonlinear relationship between the data and the unknowns can be approximated using the Taylor series truncated at the first order as follow (Menke, 1984):

$$\emptyset_k = g_k(m_0) + \sum_{i=1}^{p} \left(\frac{\partial g_k}{\partial m_i}\right) \Delta m_i + \sum_{j=1}^{o} \left(\frac{\partial g_k}{\partial O_j}\right) \Delta O_j + \sum_{r=1}^{R} \left(\frac{\partial g_k}{\partial Z_i}\right) \Delta Z_r \quad (7)$$

where the first part is the initial model, followed by the approximation of petrophysical, zone, and geometrical parameters, respectively.

Integration between MFV-cluster and interval inversion

We introduce a method to analyse the results of MFV-clustering each iteration to define the layers' continuity and by turn the layer's boundaries. We define the absolute difference between two clusters labels L_i and L_j for two successive data points d_i and d_j as delta. Based on a predefined threshold value, we group the labels with a delta that are lower than a threshold value or equal to zero. This grouping forms a set S, which consists of labels Li that satisfy the condition (delta<=threshold) for some other labels Lj within the vertical well-logging dataset. A layer is defined as a set of datapoints di corresponding to Li labels that belong to S. To further prediction of layers parameters, an interval inversion performs for the grouped data points in each layer. Thanks to the high overdetermined ratio of the interval inversion technique, the model parameters can be extended to include the zone parameters. The zone parameters are represented by one expansion coefficient of the grouped data points within each layer. While the petrophysical parameters are represented using a number of series expansions multiplied by an orthogonal polynomial function to capture changes within the depth interval. Finally, the previous workflow will be repeated to constrain the results of the interval inversion to the actual layers# coordinates extracted from the convergence of the MFV-clustering.

Application of the workflow on a synthetic dataset

In the beginning, the stability and robustness of the MFV-clustering were tested using a synthetic dataset filled with 30% outliers. Table 1 shows that the Steiner distance has a lower error as well as a smaller range compared to the Euclidean distance. Besides that, the Steiner distance shows a precise mean and lower standard deviation, which guarantees stability in the location of the updated centroids and robustness against the implemented outliers.

Table 1 *Statistical evaluation of both Euclidean and Steiner distances.*

	Mean	Standard deviation	Range	SSE
Euclidean distance	3.4	5.5	40.4	1522.3
Steiner distance	1.6	1.5	9	547.7

The proposed algorithm was tested using a synthetic well-logging dataset contaminated with 3% Gaussian noise. The synthetic model consisted of a three layers model of two sandstone layers filled with hydrocarbon with different saturation percentages with one embedded shale layer. The synthetic well log data of the first layer were calculated according to a sandstone layer filled with hydrocarbon, while the other sandstone layer was supposed to be partially filled with water. Figure 1 shows the fitting between the actual and predicted data and the layers detected from the cluster phase (last track).

Application of the workflow on gas-bearing reservoir

The real case represents a wireline logging dataset recorded for the Jurassic gas-bearing reservoir located in the Northwestern part of Egypt. The reservoir is considered a tight sand reservoir with a high degree of heterogeneity because of the diagenetic processes. The reservoir quality is affected by the illitization problem as well as quartz overgrowth. The proposed workflow was used to optimize the cementation exponent as a zone parameter as well as the prementioned petrophysical parameters. Figure 2 shows the fitting between actual and predicted data with extracted intervals coordinates in the last track, while figure (3 - left) shows the predicted parameters. Figure (3 - right) shows the convergence of the data distance.

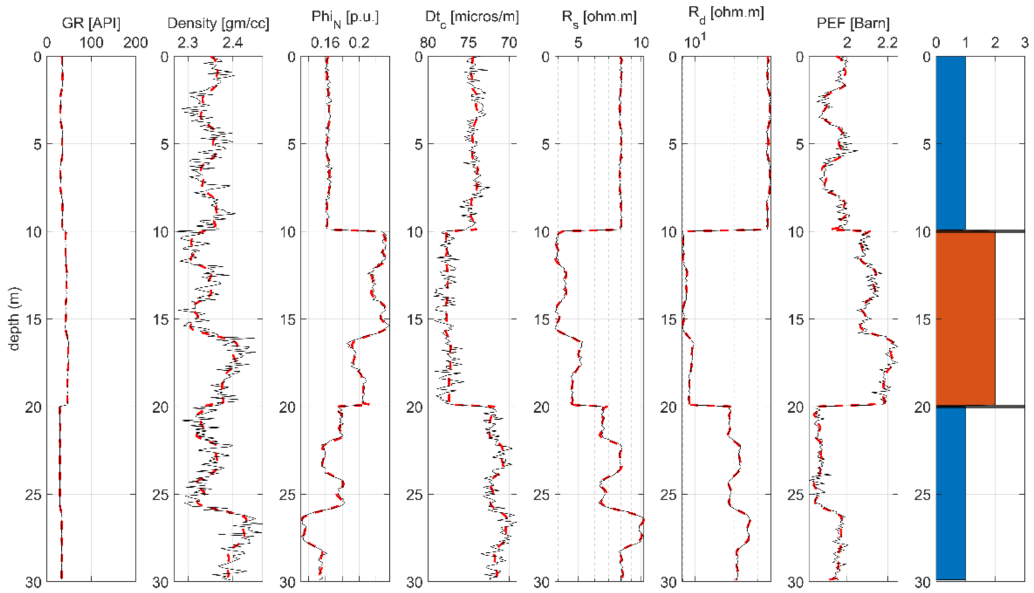

Figure 1 *The fitting between actual (solid black line) and predicted (red dashed line) wireline logging data in the synthetic case. (Iteration 10).*

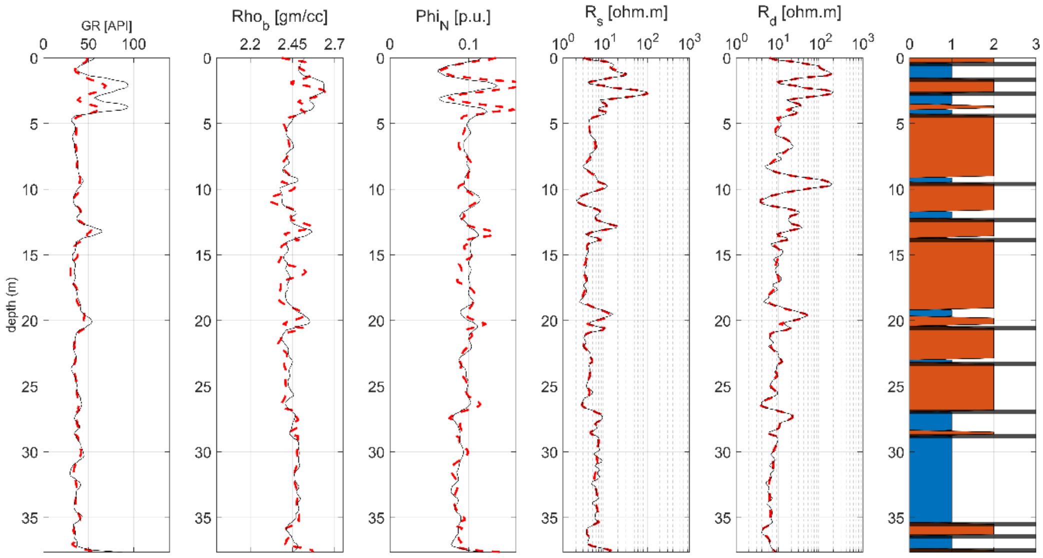

Figure 2 *The fitting between actual (solid black line) and predicted (red dashed line) wireline logging data in gas-bearing reservoir case. (Iteration 20).*

Conclusion

The integration between the MFV clustering and interval inversion could predict automatically and simultaneously the petrophysical, zone, and geometrical parameters of the borehole geophysical dataset in both cases of noisy synthetic and real datasets. In the case of the gas-bearing reservoir, the predicted parameters show that the reservoir consists mainly of sandstone layers with different rock quality. Therefore, the gas-bearing reservoir is a heterogenous reservoir in which the cementation exponent cannot be assumed to be constant, but it ranges from 2 to 2.4. The data distance between the calculated and actual borehole data set is 8%.

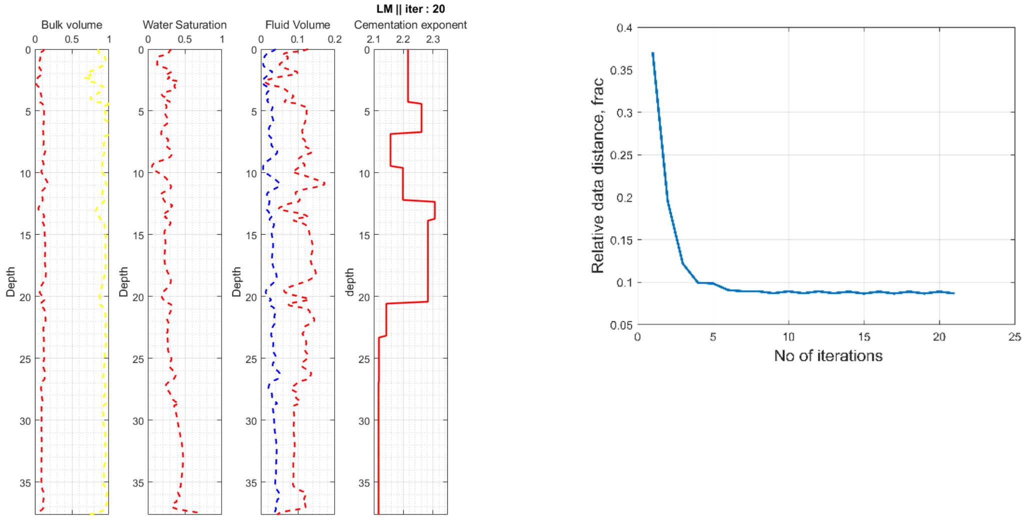

Figure 3 *The petrophysical and zone parameters prediction of the gas-bearing reservoir after Iteration 20 (left), and the data distance convergence (right).*

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References

Dobróka, M., & Szabó, N. P. (2011). Interval inversion of well-logging data for objective determination of textural parameters. *Acta Geophysica*, *59*(5), 907–934. https://doi.org/10.2478/s11600-011-0027-z

Doveton, J. (2001). *All Models Are Wrong, but Some Models Are Useful: "Solving" the Simandoux Equation*.

Lima, L., Bize-Forest, N., Evsukoff, A., & Leonhardt, R. (2020). Unsupervised deep learning for facies pattern recognition on borehole images. *Offshore Technology Conference Brasil 2019, OTCB 2019*. https://doi.org/10.4043/29726-ms

Menke, W. (1984). Geophysical data analysis: Discrete inverse theory. In *Geophysical Data Analysis: Discrete Inverse Theory*. Academic Press Inc. https://doi.org/10.1016/0040-1951(86)90212-x

Steiner, F. (1991). *The Most Frequent Value. Intro- duction to a Modern Conception Statistics*. Akademia Kiado.

Szabó, N. P., Braun, B. A., Abdelrahman, M. M. G., & Dobróka, M. (2021). Improved well logs clustering algorithm for shale gas identification and formation evaluation. *Acta Geodaetica et Geophysica*, *56*(4), 711–729. https://doi.org/10.1007/s40328-021-00358-0

Szabó, N. P., & Dobróka, M. (2020). Interval inversion as innovative well log interpretation tool for evaluating organic-rich shale formations. *Journal of Petroleum Science and Engineering*, *186*(November), 106696. https://doi.org/10.1016/j.petrol.2019.106696