EEI ATTRIBUTES FOR FLUID DISCRIMINATION USING FUZZY LABELED MULTICLASS SUPPORT VECTOR MACHINE

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ABSTRACT

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In exploration seismology, automatic seismic facies analysis to discriminate different facies and fluid content is an essential task to reduce future drilling risks. There are different seismic attributes as learning features and various learning methods for automatic seismic facies analysis. Previous studies have proved that selecting efficient seismic attributes is more crucial than the learning method. Therefore, it is logical to pay more attention to the choice of proper attributes. The extended elastic impedance (EEI) attributes belong to prestack seismic attributes, and they are functions of compressional velocity, shear velocity, density, and chi angles. The Chi angle is the virtual incident angle and changes between -90 to +90 degrees.

The innovative method demonstrates the role of fluid replacement modeling (FRM) for the supervised selection of EEI attributes at suitable chi angles as input features to train an intelligent model for the discrimination of reservoir fluid contents.

The method starts with FRM to model different fluid contents of the reservoir (100% brine, 100% oil, and 100% gas) using borehole data. Then, efficient EEI (Chi) logs are selected according to the results of the EEI template analysis. Thus, EEI seismic attributes at selected Chi angle are calculated from prestack seismic data by amplitude versus offset (AVO) analysis and EEI inversion. Then, labeling of the EEI attributes is performed by fuzzy c-mean clustering (FCM). By considering membership functions, a fuzzy concept is an appropriate tool for soft clustering and an appealing method for seismic interpretation. Afterward, a classifier model of the multiclass support vector machine (SVM) is trained using the fuzzy labeled samples to predict the fluid type of unseen data.

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The method was applied to a 3D prestack seismic data of an oil sand reservoir in the Persian Gulf to predict the fluid distribution map at the top of the reservoir. The reservoir contains a considerable amount of gas cap. Only one borehole data drilled in the oil column is available for FRM and fluid EEI template analysis. The available fluid distribution map confirms the accuracy of the resulted fluid distribution map based on the modeling of all the wells in different locations of the reservoir. This confirmation proves the application of the proposed method in fluid pore identification.

KEY WORDS: seismic facies analysis, fluid discrimination, extended elastic impedance, fuzzy clustering, multiclass support vector machine, fluid replacement modeling.

INTRODUCTION

In recent years, different intelligent systems were introduced in the petroleum industry to perform seismic facies analysis and reservoir characterization. They are powerful tools for extracting quantitative relations between seismic attributes as input data and seismic facies as output data. Despite their low resolution, the seismic data is used for quantitative reservoir analysis because of their areal coverage (Chopra and Marfurt, 2007). So, one of the significant issues in evaluating a reservoir is linking seismic data with the well data's petrophysical properties using intelligence systems. Several works have been conducted using different learning methods to predict characteristics of the reservoirs and seismic facies analyses using seismic attributes (Hashemi et al., 2008; Na'imi et al., 2014; Hashemi and Beukelaar, 2017; Wang et al., 2017; Wrona et al., 2018; Zhao, 2018). The biggest challenge in seismic interpretation is the discrimination of different fluid contents and their spatial distribution (Sharifi and Mirzakhanian, 2019). Previous studies have proved that for robust and reliable reservoir characterization, selecting appropriate seismic attributes is more important than the learning algorithm (Barnes, 2007). Also, according to Barnes and Laughlin (2002), the performance of a learning algorithm decrease by increasing the dimensionality of input features. Therefore, it is logical to pay more attention to selecting appropriate and efficient attributes. Various methods have been employed to select seismic attributes or input features for learning systems (Bagheri et al., 2013; Mardan et al., 2017; Hadiloo et al., 2018; Shang et al., 2019). Extended elastic impedance (EEI) analysis is one of these methods which can provide prestack seismic attributes with a strong link to a particular reservoir property (Whitcombe et al., 2002; Mirzakhanian et al., 2015; Samba et al., 2017; Sharifi et al., 2019; Sharifi and Mirzakhanian, 2019; Mirzakhanian and Hashemi, 2022a-2022b).

The fuzzy systems are applicable to deal with uncertainty and inaccuracy by considering membership functions for input samples. Some researchers have discussed the application of soft computing and fuzzy concepts in geophysics and quantitative seismic facies analysis (Aminzadeh and Winkelson, 2004; Aminzadeh and de Groot, 2004; Aminzadeh and de

Groot, 2006; Hashemi, 2010, 2012; Hadiloo et al., 2018; Mirzakhanian and Hashemi, 2022b).

In this paper, the fluid replacement modeling (FRM) is performed to select efficient seismic attributes in a supervised manner for automatic identification of fluid distribution map. In previous studies, selecting seismic attributes for facies analysis was an unsupervised approach (Mardan et al., 2017; Zhao et al., 2010; Shang et al., 2019). Hence, fluid replacement modeling is carried out to build three saturation scenarios in terms of pore fluid types (gas, oil, and brine) to select the most efficient EEI attributes. The most differentiated EEI attributes at certain Chi angles are chosen according to the results of EEI changes pattern for each saturation scenario (fluid EEI template analysis). Then, AVO analysis and EEI inversion are performed on prestack seismic data according to the outcome of fluid EEI template analysis to prepare certain EEI attributes maps for the top of the reservoir. Afterward, the fuzzy c-mean (FCM) clusters the selected samples of prepared EEI maps into three segments. This is followed by training a support vector machine (SVM) classifier, according to the SVM advantages in classification (Wrona et al., 2018; Nishitsuji and Exley, 2019), to predict the unseen data.

In the proposed method, there is no need to use unsupervised feature selection methods such as attributes cross-correlation, principal component analysis (PCA), Fisher discriminant analysis (FDA), etc. Also, only one well with density, compressional, and shear velocity data is used for fluid EEI analysis as a feasibility study to select the efficient EEI attributes. In this study, the reservoir is considered homogeneous for simplification. It is worth noting that rock-physics modeling is applicable if needed to model the heterogeneity of a reservoir. Also, in cases with more boreholes available, it is recommended to use all the wells data to perform EEI analysis.

This methodology is employed on a 3D prestack seismic data belonging to an Iranian oil field in the Persian Gulf. For confidential issues, only one borehole data with shear velocity is available for FRM and EEI analysis. To choose the optimum SVM kernel, the validity and calculation time are analyzed for each kernel. The accuracy of the fluid map obtained from the proposed method is validated by a fluid spatial distribution map based on the modeling of all available wells.

THEORY AND METHOD

Whitcombe (2002) introduced R_{EEI} (χ) or EEI reflectivity as a modified two-term linearized Zoeppritz equations (1919) as the following:

$$R_{EEI}(\chi) = A \cos \chi + B \sin \chi \quad , \tag{1}$$

where A and B are intercept and gradient. The chi angle (χ) is a theoretical incident angle that changes between -90 and 90 degrees. By introducing some reference constants, he obtained the normalized dimensionless impedance values for all 181angles. Therefore, a new-scaled formula equivalent to the EI (Connolly, 1999) is developed for a new parameter called the EEI spectrum.

$$\mathrm{EEI}(\chi) = \bar{V}_p\, \bar{\rho} \left[(\frac{V_p}{\bar{V}_p})^p (\frac{V_s}{\bar{V}_s})^q (\frac{\rho}{\bar{\rho}})^r \right] \quad , \tag{2}$$

where

$p = cos\,\chi + sin\,\chi, q = -8K\, sin\,\chi$, and $r = cos\,\chi - 4K\, sin\,\chi\,, K = \left(\frac{V_s}{V_p}\right)^2$.

EEI analysis by computing the impedance values beyond the physically observed range of incident angles is beneficial for discriminating different lithologies and fluid types (Whitcombe et al., 2002; Mirzakhanian et al., 2017; Yenwongfai et al., 2017; Sharifi et al., 2019). Connolly (2017) indicated equivalent chi angles and the weighting of different relative rock properties for a set of elastic properties. Later on, Sharifi and Mirzakhanian (2019) innovated Full-angle extended elastic impedance to indicate fluid type in a carbonate reservoir by rock physics templates.

Different rock physical modeling techniques have been presented based on theoretical, empirical, or hybrid models (Kuster and Toksöz, 1974a,b; Xu and White, 1995; Mavko et al., 2009; Saberi et al., 2009; Xu and Payne, 2009). For fluid replacement modeling, the initial set of velocities (compressional and shear) and density data corresponding to a rock having an initial fluid content are used to compute the velocities and density data of the rock with another type of fluid. Often these initial data sets are measured from the well logs or theoretical models (Avseth et al., 2006).

The fuzzy version of the k-means algorithm is introduced as FCM as an unsupervised method in pattern recognition and soft data clustering. The fuzzy techniques by using membership functions for each sample of data improve the certainty of clusters (Hashemi, 2012). The data samples separate into overlapping groups according to the membership degrees to better describe data structure. Therefore, the results of soft clustering methods are more real compared to the hard clustering methods (Bora and Gupta, 2014). Shape, volume, and the number of clusters are crucial issues for FCM. The optimum number of clusters is indicated according to the general knowledge of the interpreter about data structure and the assessment of some validity indices. The support vector machine (SVM) is a supervised machine learning approach to perform classification and regression tasks by generating an optimal separation between two classes with maximum margin. SVM as an effective classifier proposed based on structural risk minimization to reduce classification risk and present a more efficient classification (Tomar and Agarwal, 2015; Salimi Sartakhti et al., 2018; Wrona et al., 2018; Nishitsuji and Exley, 2019). Using SVM over other approaches is a simpler and more efficient algorithm. However, it suffers from drawbacks such as sensitivity to noise and outliers, an, unbalanced dataset and high computational time. But, various modifications have been carried out in SVM to overcome the drawbacks above (Li et al., 2015; Khemchandani et al., 2016). The SVM is a global solution to classify the data patterns of different classes and is inherently a well-known technique for binary classification. But, researchers successfully have extended it to the multiclass problem (e.g., Tomar and Agarwal, 2015; Khemchandani and Sharma, 2016; Wrona et al., 2018). The database is further segmented into training and testing data sets to evaluate classification. In learning algorithms, the training data is used to construct the classifier, while the testing data is employed for its evaluation.

This study evaluates the role of supervised selection of EEI attributes for fluid identification using FCM clustering and SVM classification. Fig. 1 presents the flow diagram of the study.

CASE STUDY

The presented method is applied to prestack seismic data belonging to an oil field in the Persian Gulf. The 3D seismic survey covers approximately 240 km^2. The final processed bin spacing is 12.5 x 12.5m. The sample rate for the data acquisition is 4ms. The maximum offset is almost 3000m with the angle coverage 0f 30 degrees at the studied time interval. Data quality is generally good over the entire time range without strong multiple interferences. The field is an anticline with northwest-southeast trending. There are more than thirty drilled wells around the field area. The reservoir consists of up to 100 m of loose sands, with interbedded shale, dolomite, dolomite ,cemented sandstones and nodular anhydrite, with an oil column of about 44 m and 18 m gas cap. For this study, only a small portion of seismic data is present. Only one well data (A-01) with shear velocity is available (due to the confidential issues) to perform fluid replacement modeling and fluid EEI template analysis. The authors have access to the fluid map modeled according to the all wells data around the anticline to validate the method. The locations and geology markers of two other wells, one in gas (A-02) and the other in the oil column (A-10), are also available but not their logging data. A seismic section that crosses these three available wells is present in Fig. 2. The sandstone reservoir is limited between two blue interpreted horizons. The gas-oil contact (GOC) at the well A-02 and oil-water contact (OWC) at the wells A-01 and A-10 are also indicated in the seismic section.

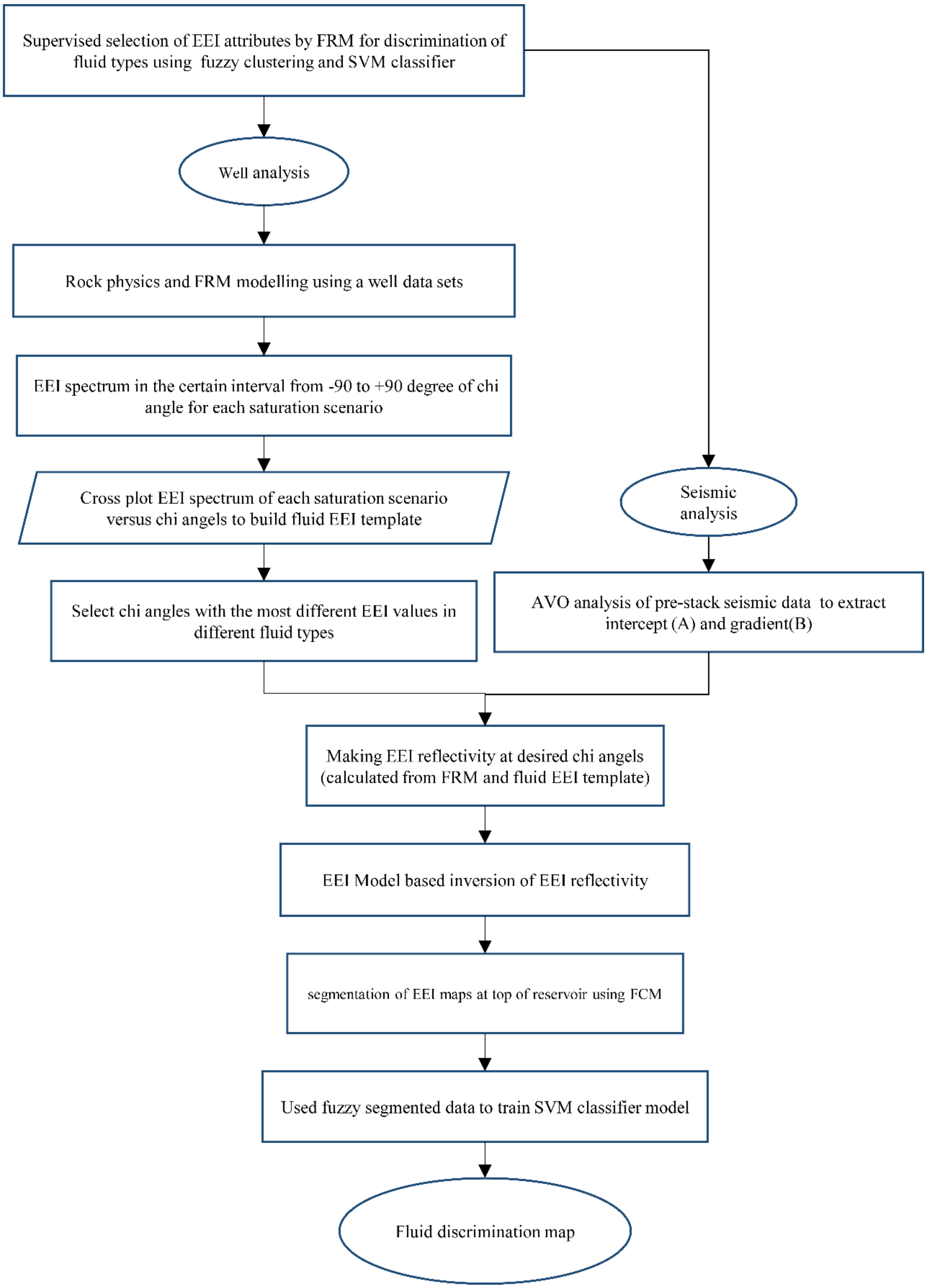

Fig. 1. The workflow of the proposed methodology.

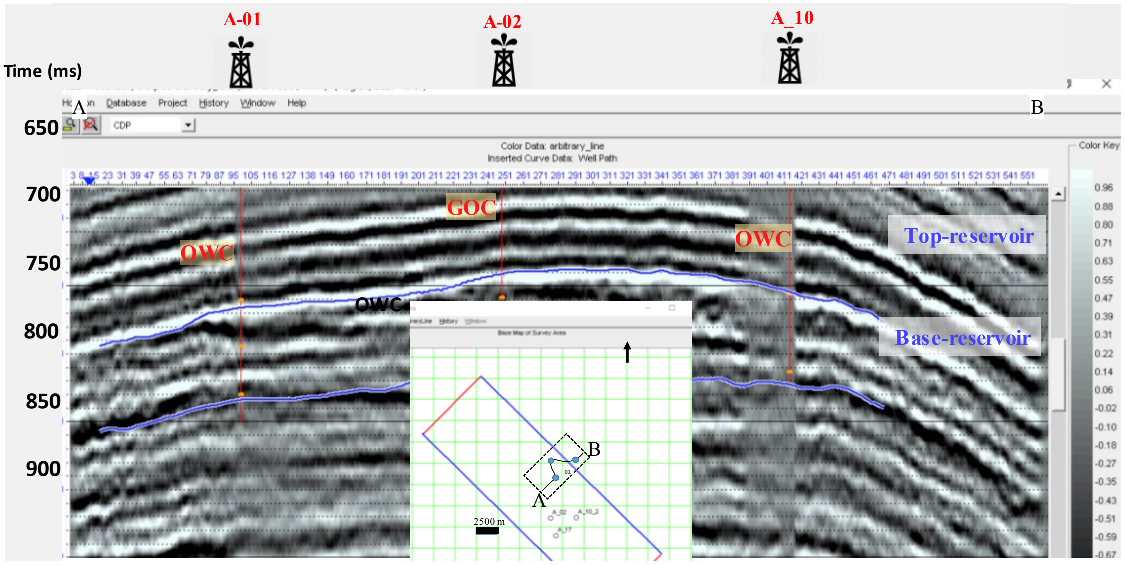

Fig. 2. An arbitrary seismic section of the field. The reservoir is located between two blue horizons. The base map shows the full coverage of seismic data. The blue points represent well locations. The dotted square indicates seismic data available for this study, and the black line shows the arbitrary line path on the map.

RESULTS

Fluid replacement modeling (FRM)

To analyze the variations of EEI versus chi angles under different scenarios (fluid EEI template), fluid replacement modeling (FRM) is performed in the reservoir interval using the A_01 data drilled in the oil column. The reservoir consists of unconsolidated sands with intervals of shale and dolomite. For FRM, mineral types and their volume fractions are taken from the petrophysical interpretation and core data. Then, the results combine using Hashin-Shtrikman's average (Mavko et al., 2009; Rein, 2015) to obtain elastic parameters of the solid rock matrix. Petroleum engineering reports and well tests provide pore fluid properties (e.g., gas-oil-ratio, salinity, etc.). Then, the fluids' elastic properties are modeled, and different phases are mixed using Wood's model, considering a homogeneous reservoir. Finally, as an essential parameter of Gassmann's equation (1951), the frame modules of dry rock are derived using measured velocities, density and porosity logs, and Gassmann theory. Fig. 3 shows the result of fluid replacement modeling for the reservoir interval along well A-01. The figure indicates that the modeled and measured data have been similar enough to validate the FRM results.

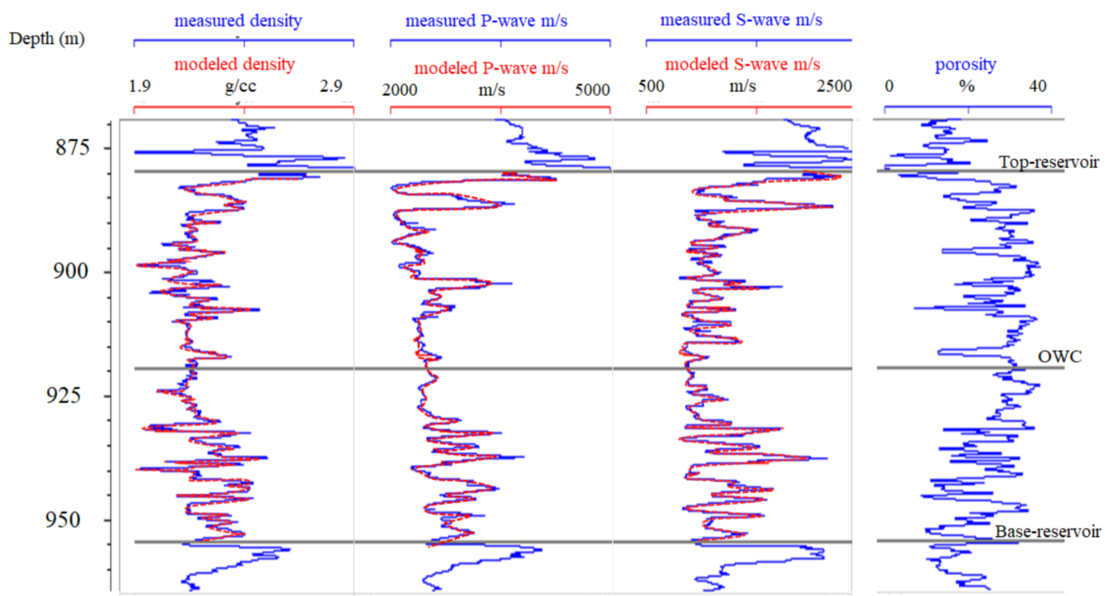

Fig. 3. Measured well log data (blue) and predicted data (red) along unconsolidated reservoir at A-01. Track 1 shows the measured and modeled density. P- and S-wave velocities are shown along tracks 2 and 3, respectively. The total porosity log is present along track 4.

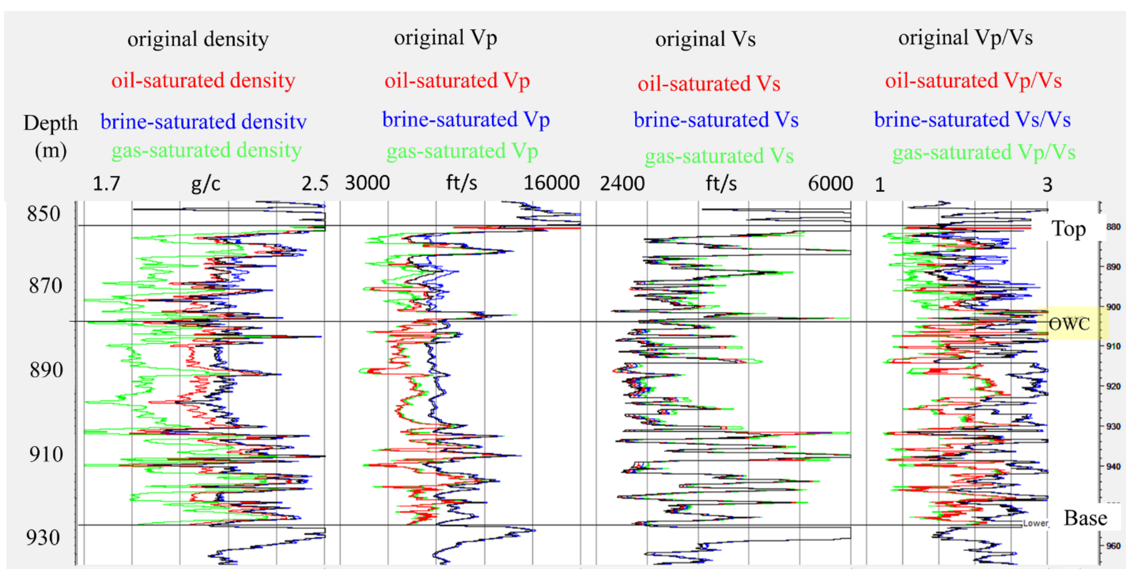

Fig. 4. Original and FRM data along the reservoir of the well A-01. Track 1 shows density logs for original data and three scenarios of fluid saturation (brine, oil, and gas). Related P-wave and S-wave velocities are shown along tracks 2 and 3, respectively. Track 4 shows Vp/Vs ratio logs for different scenarios. As the reservoir is oil saturated initially, the modeled data is more similar to the oil saturated scenario logs at the upper part of the reservoir. However, by increasing the depth and percentage of water saturation, the modeled data is more similar to the brine saturated scenario logs.

EEI analysis

In this step, fluid replacement modeling is compared to the measured data to validate the results. The results confirmed that the well log data are adequately sensitive to fluid type and saturation changes in the reservoir. Therefore, the EEI spectrums related to each saturation scenario (original, 100% oil, 100 % gas, and 100% brine) are built in the reservoir interval using calculated logs by FRM and eq. (2) (Fig. 5).

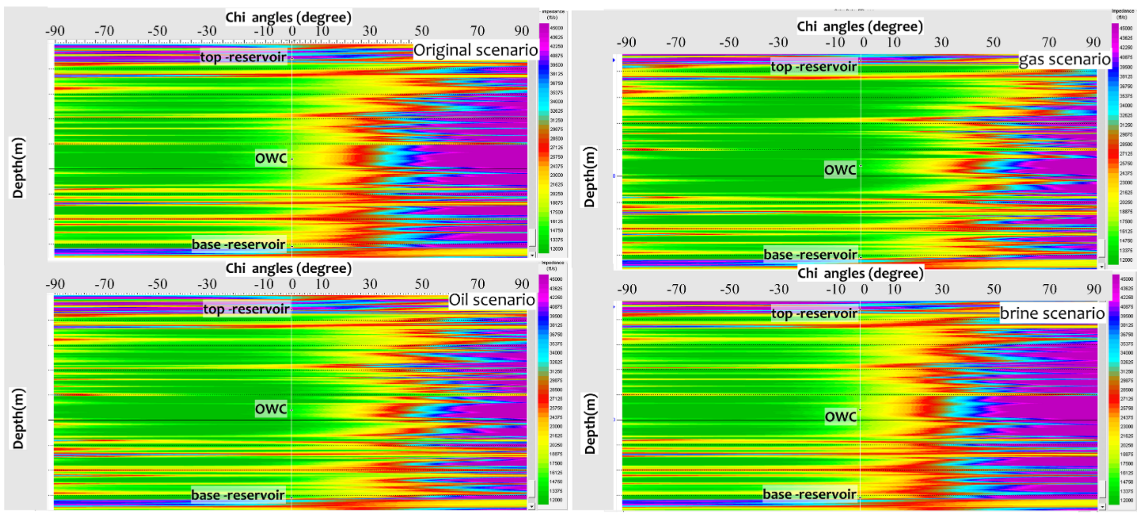

Fig. 5. EEI spectrum for different scenarios (original, 100% oil, 100% gas and 100% brine) using eq. (2). The color scale indicates EEI values at different depth and chi angles. The different EEI spectrum for different scenarios is clear.

Then the EEI logs at the top of the reservoir are extracted from each EEI spectrum for EEI template analysis. EEI data for different fluid contents plots versus chi angles in a single cross-plot (Fig. 6). Because the well A-01 has been drilled in an oil-saturated zone of the reservoir with low percentage of water saturation (avg. 10-20%), the EEI trend of the original scenario resembles the curve for the fully oil-saturated scenario in the fluid EEI template.

According to Fig. 6, EEI values for different fluid scenarios at most of the Chi angles, except at 55 degrees, are different. It indicates the efficiency of EEIs as prestack attributes to discriminate fluid content. According to the EEI template analysis, two chi angles 90° and +90°) are chosen. As it is clear, at –90°, the value of EEI for the gas scenario is more than two other scenarios, and at +90°, the values of the brine scenario are the most. EEI (+90) is representative of the gradient. So, these two EEI logs/attributes provide efficient input features for the learning algorithm for this case. The selection of more angles only increased the run time with no further improvement in the algorithm. Accordingly, angle +45° as the representative of Vp/Vs is not selected due to the similarity of its relative values to values of +90°.

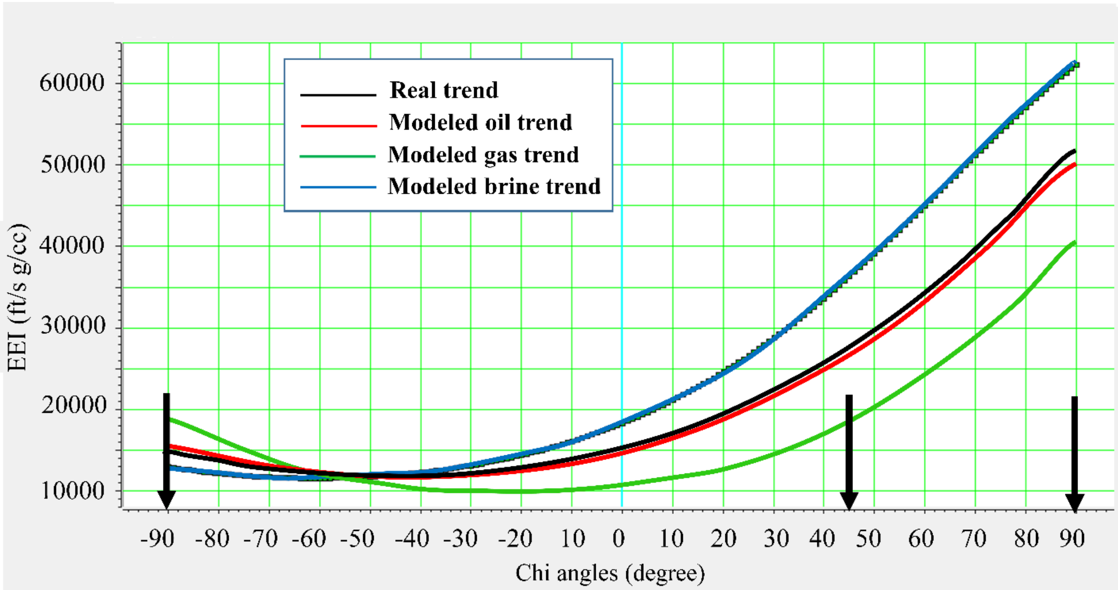

Fig. 6. EEI values changes from -90° to +90° of Chi angle for the different scenario of fluid type at the top of the reservoir calculated by the well A-01 data. Since the well A-01 has been drilled in the oil, the trends of EEI for the oil scenario and the real one are almost similar. Black arrows indicate angles –90°, +45° and +90°.

EEI inversion

After selecting proper EEI attributes, the EEI reflectivity cubes are built having intercept and gradient from AVO analysis [eq. (1)] at these two certain angles. Furthermore, well to seismic correlation, low-frequency modeling and wavelet extraction convert each EEI reflectivity into elastic impedances.

A synthetic seismogram is generated by convolving the extracted wavelet with a time-reflectivity series derived from the well log data to improve well tying. Next, the time-depth relation is optimized according to the correlation coefficient between real seismic and the synthetic seismic data along the well path. Then, a low-frequency model is built based on the well logs and interpreted horizons to compensate for the deficiency of low-frequency information in seismic data. Finally, EEI inversion is performed on each EEI reflectivity using model-based inversion. The outputs of the inversions are EEI cubes at two selected angles [i.e., EEI (–90°) and EEI (+90°)]. For more details of EEI inversion, readers are recommended to study Whitcombe (2002), Sharifi et al. (2019), and Sharifi and Mirzakhanian (2019).

Preparation of input features

In this step, EEI amplitude maps related to the top of the reservoir are prepared (Fig. 7). Then, adequate samples from different reservoir locations are selected as input features for FCM clustering from those two maps. Each cluster represents one fluid type (i.e., gas, oil, or brine). Therefore, there is no need to employ and assess different validity indices to select the number of clusters before fuzzy segmentation. The output of this stage is fuzzy labeled data with two learning features as input for SVM classification.

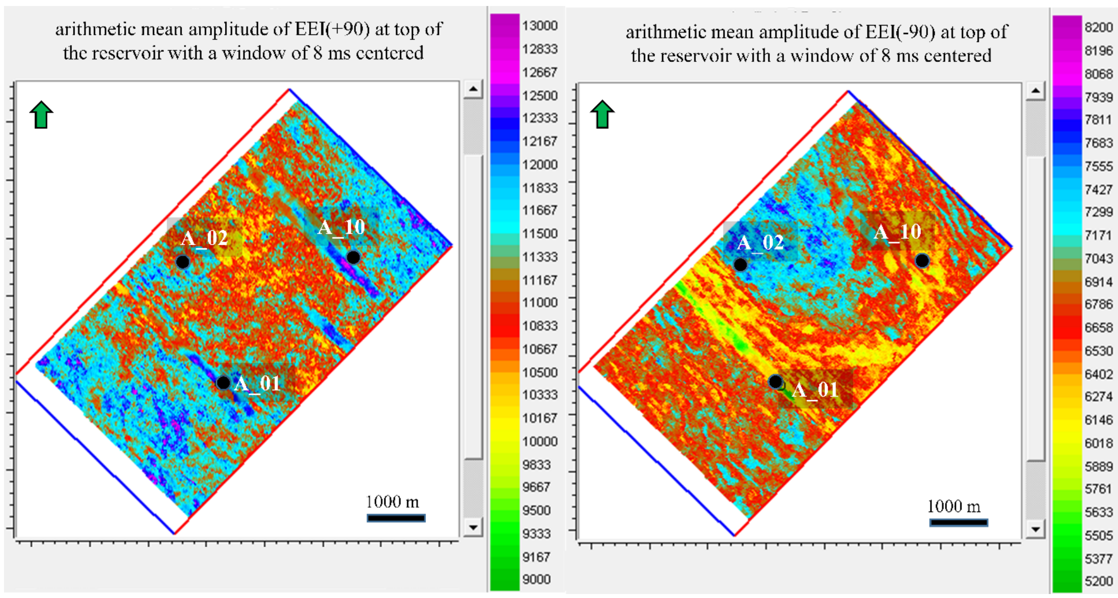

Fig. 7. EEI changes amplitude map for two Chi angles selected according to fluid EEI template of different saturation scenarios. The EEI template is created based on rock-physics modeling and FRM.

SVM classifier

The prepared data in the previous session is provided to SVM classifiers learners in Matlab (2021a) to detect fluid types. To evaluate the accuracy of classifiers, the data is further segmented into training and testing data sets using K-fold. In the K-fold validation technique, the data is divided into ten subparts of the same size and dimensions (10-fold), and ten iterations of the cross-validation process are performed. In each iteration, one fold is used as testing data while the other remaining forms the training data. The accuracy is computed for each iteration, and the absolute accuracy is obtained by averaging the accuracy of all cycles.

Different multiclass SVM classifiers with different kernels using one versus one approach are employed. The accuracy and calculation time for each one is presented in Fig. 8. According to this figure, SVM with a linear kernel provides the admissible accuracy results in an acceptable running time. Therefore, the linear SVM model with one versus one approach is finally selected to predict unseen data.

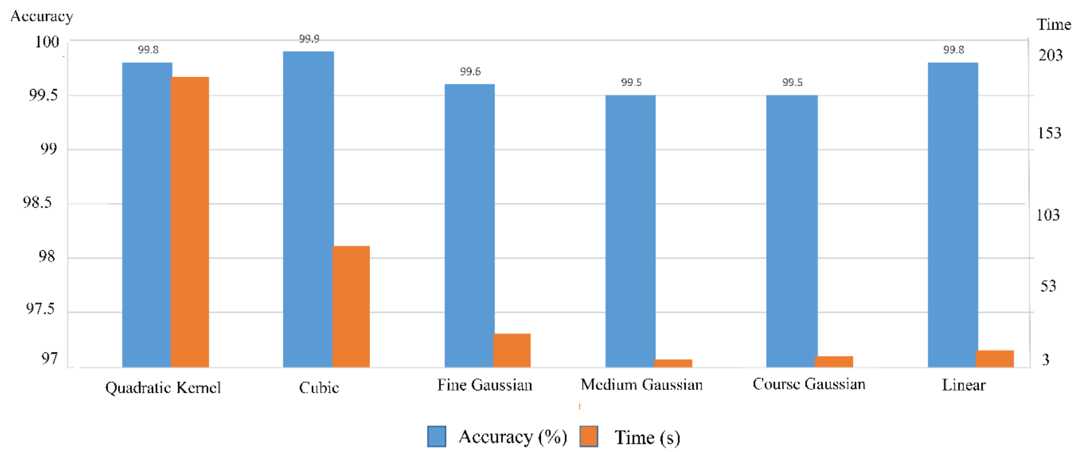

Fig. 8. Overall accuracy and calculation time for different multiclass SVM classifiers to discriminate fluid types.

DISCUSSION

In this case study, The FRM results are used to select certain angles of the EEI spectrum as seismic attributes (fluid EEI template analysis). The elastic parameters of the reservoir are modeled using only the well A-01 data. By replacing different fluid types (using Gassmann's equation), the behavior of each fluid scenario is modeled and presented in the fluid EEI template (Fig. 6). The EEI template helps select limited but efficient seismic attributes in a supervised manner.

EEI attributes maps related to the top of the reservoir are extracted from prestack seismic. The maps are segmented into three clusters using FCM clustering. The seismic data is inherently degraded with some range of noise and uncertainty. In addition, the fluid contents of the reservoir change gradually, and the fluids' boundaries are not crisp. For such cases, fuzzy concepts and soft computing are more practical.

The segmentation is performed on only a tiny part of the available data. Then, SVM classification is applied to the fuzzy segmented data. According to the analysis of different multiclass SVM classifiers and the results of figure 8, the linear SVM model is trained and used to predict unseen data, considering the trade-off between time and accuracy. The predicted fluid map using the SVM classifier is present in Fig. 9. To evaluate the privilege of the presented method, we have compared the results with a fluid distribution map prepared by modeling all the productive wells around the studied area. The similarity of these two fluid maps is addressed in this figure. The high degree of correlation between these maps indicates the enormous potential of the proposed method in fluid discrimination using proper EEI attributes. The minor differences between these two maps are due to undershooting areas. Two other wells, A-02 and A-10, located in the gas and the oil part of the reservoir, respectively, are present as witnesses to validate the resulted map. For confidential issues, we do not have access to the location of other wells. Seismic data coverage is considerably higher than the sparse well data sets. Therefore, the map resulting from the proposed method has a higher resolution between boreholes than the map from borehole modeling.

The most significant advantage of the innovative method is that the feasibility study and analysis of seismic attributes can be performed using only one well data. This is a vital issue in a reservoir's exploration and development phases with limited numbers of drilled wells.

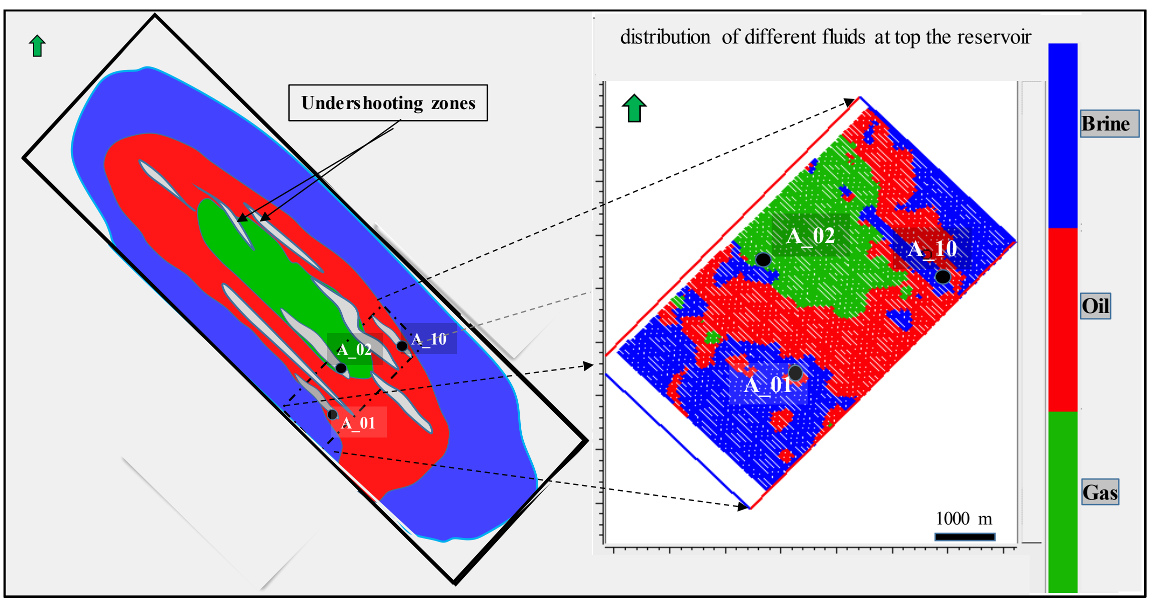

Fig. 9. Spatial discrimination map of different fluids at the top of the reservoir based on well data modeling is present on the left side to compare with the map resulting from the presented method (right side). The slight difference between the two maps is due to undershooting areas (gray polygons). In addition, the spatial resolution of the map resulting from seismic data between boreholes is more than the map created from sparse well data modeling.

CONCLUSION

The paper presented a new workflow to generate fluid maps for a clastic reservoir from seismic data using an integration between EEI attributes, fussy clustering, and SVM algorithm using FRM. Here, an innovative approach has been taken to use EEI template analysis for fluid discrimination. Seismic attributes in learning methods are more crucial than classifiers. So, there has been a special focus on selecting proper seismic attributes. For this purpose, a feasibility study was performed by fluid replacement modeling and fluid EEI template analysis to select efficient EEI attributes. The equivalent EEI maps were extracted from prestack seismic data and were segmented into three clusters (i.e., brine, oil and gas) using FCM. Then, a multiclass SVM classifier was trained to predict the unseen data.

The map from this workflow was comparable to the map from the modeling of all the wells around the studied oil field, confirming the proposed method's efficiency and validity. Only one borehole data was available for fluid EEI template analysis and EEI attribute selection step in this study. So, this approach could be of high importance in the exploration oil fields with a limited number of wells available. This method can be used for any geological formation after FRM and EEI analysis feasibility study. It is worth mentioning that rock-physics modeling helps analyze EEI trends in similar cases with limited boreholes available. For case studies with more boreholes, it is highly recommended to use all the wells available to improve the selection of efficient EEI attributes.

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