3D Petrophysical modeling using complex seismic attributes and limited well log data

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Summary

A method for 3D modeling and interpretation of log properties from complex seismic attributes (obtained from 3D post stack seismic data) is developed by integrating Principal Component Analysis and Local Linear Modeling. Complex seismic attributes have non-linear relationships with petrophysical properties of rocks. These complicated relationships can be approximated using statistical methods.

This method has been tested successfully on real data sets. Log properties (sonic, gamma ray density etc.) were predicted at the location of the second well (blind well test). It has proved to work with limited log information (data from one well) whereas conventional methods, such as geostatistics, used for this purpose need well log information from several wells to correlate seismic and well data. Once the performance of the model is verified by blind well test, 3D log volumes can be calculated from 3D seismic attribute data.

Introduction

Seismic data are routinely and effectively used to estimate the structure of reservoir bodies. Also they have been increasingly used for estimating the spatial distribution of rock properties. Many authors have investigated the possible relations between individual seismic attributes and rock properties (or structural indications). Taner et al. 1994 published a list of such relations. The idea of using multiple seismic attributes to predict log properties was first proposed by Schultz et al. (1994). They used log data from 15 wells to train with seismic attributes and predict rock properties. Hampson et al. (2001) also explains use of different neural networks for multi-attribute analysis and reservoir property prediction.

While we know that seismic signals features are directly caused by rock physics phenomena, the links between these two are complex and difficult to derive theoretically. Seismic response depends on many variables, such as temperature, volume of clay, overburden, pressure, nature and geometry of the layering, and other factors which affect elastic and absorption response. These complex relations can vary from one layer to another, and even within a single layer or reservoir compartment (Schultz et al., 1994). Schultz et al. (1994) showed that simultaneous use of seismic attributes with well log data leads to better prediction of reservoir or rock properties, compared to estimations using only well data. A reasonable way to combine seismic attributes and well log data for property prediction should include a statistical method.

Methodology

The data used in this study belongs to a shaly sandstone reservoir in the Middle-East. Two wells were selected for this study. One for training the network and the other one for cross-validation (the distance between two wells is approximately 4 km).The main seismic attributes that are used in this study are amplitude envelope, first and second derivative of amplitude, quadrature trace, instantaneous frequency and dominant frequency. Attribute data are normalized and reduced using principal component analysis before modeling task. The proposed unsupervised clustering method in this paper is Fuzzy-Self Organizing Map (FSOM) in which the Gustafson-Kessel algorithm is integrated in the learning and updating strategies of the Kohonen Self Organizing Maps (Kohonen, 1989). Bezdek et al. (1992) introduced a FSOM method by combining the FCM clustering in the learning rate and updating strategies of the SOM and showed the superiority of this method compared to SOM. Also, Hu et all. (2004) shows that FSOM is more efficient than the SOM and vector quantization in both speed and accuracy.

In this method, equation (1) is devised for updating the centers of clusters (Bezdek et al., 1992):

$$c_{ij}(t+1) = c_{ij}(t) + \frac{\sum_{l=1}^{M} \mu^{\upsilon}{}_{lj}(t).(u_{li} - c_{ij}(t))}{\sum_{l=1}^{M} \mu^{\upsilon}{}_{lj}(t)} \quad (1)$$

where

$$\mu_{lj}(t) = \frac{\dfrac{1}{D^2_{lj\Sigma_j}}}{\sum_{m=1}^{K} (\dfrac{1}{D^2_{lm\Sigma_j}(t)})} \quad (2)$$

$$D^2_{lj,\Sigma_j}(t) = \| u_{li} - c_{ij} \|^2_{\Sigma_j} = \sum_{i=1}^{N} (u_{li} - c_{ij}(t))^T \Sigma_j (u_{li} - c_{ij}(t)) \quad (3)$$

$$\Sigma_j = F_j^{-1}.(v_j \det(F_j))^{1/N} \quad (4)$$

$$F_j = \frac{\sum_{l=1}^{M} \sum_{i=1}^{N} \mu^{\upsilon}_{lj} (u_{li} - c_{ij}(t))(u_{li} - c_{ij}(t))^T}{\sum_{l=1}^{M} \mu^{\upsilon}_{lj}} \quad (5)$$

where *l=1,…,M* is the number of data points, *j=1,…,K or C* is the number of clusters and *i=1,…,N* is the dimension of the input data (number of attributes), c is the center of cluster, μ is the membership degree of data samples and t is the number of iteration. (Nelles, 2001).

After clustering the data, centers can be embedded in the hidden layer of the local linear neuro-fuzzy networks. The network structure of a local linear neuro-fuzzy model is depicted in Figure.1. Each neuron realizes a local linear model (LLM) and an associated *validity function* that determines the region of validity of the LLM. The outputs of the LLMs are (Nelles, 2001)

$$\hat{y}_{ki} = w_{i0} + w_{i1}u_{k1} + w_{i2}u_{k2} + \ldots + w_{ip}u_{kp}, \quad (6)$$

$$k = 1, \ldots, N, \qquad i = 1, \ldots, M$$

where N is the number of the data samples, M is the number of the local linear models (in other words, clusters), p is the dimensionality of the input space (number of attributes) and w_{ij} denotes the LLM parameters for neuron i.

The validity functions form a partition of unity, i.e., they are normalized such that

$$\sum_{i=1}^{M} \bar{\Phi}_i(u_k) = 1 \quad (7)$$

The output of a local linear neuro-fuzzy model is:

$$\hat{y}_k = \sum_{i=1}^{M} \underbrace{(w_{i0} + w_{i1}u_{k1} + w_{i2}u_{k2} + \ldots + w_{ip}u_{kp})}_{\hat{y}_{ki}} \Phi_i(u_k) \quad (8).$$

Therefore, the network output is calculated as a weighted sum of the outputs of the local linear models where $\Phi_i(\cdot)$ are interpreted as the operating point dependent weighting factors. The neuro-fuzzy network interpolates between different LLMs with the validity function. The validity functions are chosen as normalized Gaussians. (Nelles, 2001).

$$\bar{\Phi}_i(u_k) = \frac{\mu_i(u_k)}{\sum_{j=1}^{M} \mu_j(u_k)} \quad (9)$$

where

$$\mu_i(u_k) = \exp\left(-\frac{1}{2}\left(\frac{(u_{k1} - c_{i1})^2}{\sigma_{i1}^2} + \cdots + \frac{(u_{k1} - c_{i1})^2}{\sigma_{ip}^2}\right)\right) \quad (10).$$

In the global estimation approach (Nelles, 2001) all parameters are estimated simultaneously by least squares optimization. The parameter vector contains all *n=M(p+1)* parameters of the local linear neuro-fuzzy model in (8) with M neurons and p inputs:

$$\underline{w} = [w_{10}, w_{11}, w_{12}, \ldots, w_{M0}, w_{M1}, \ldots, w_{Mp}]^T \quad (11)$$

The associated regression matrix X for N measured data points is (Nelles 2001):

$$\underline{X} = [\underline{X}_1^{(sub)}\ \underline{X}_2^{(sub)} \ldots \underline{X}_M^{(sub)}] \quad (12)$$

with

$$\underline{X}_i^{(sub)} = \begin{bmatrix} \Phi_i(u_1) & u_{11}\Phi_i(u_1) & u_{12}\Phi_i(u_1) & \ldots & u_{1p}\Phi_i(u_1) \\ \Phi_i(u_2) & u_{21}\Phi_i(u_2) & u_{22}\Phi_i(u_2) & \cdots & u_{2p}\Phi_i(u_2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \Phi_i(u_N) & u_{N1}\Phi_i(u_N) & u_{N2}\Phi_i(u_N) & \cdots & u_{Np}\Phi_i(u_N) \end{bmatrix}$$

(13).

The model output $\underline{\hat{y}} = [\hat{y}_1\ \hat{y}_2 \cdots \hat{y}_N]^T$ is given by

$$\underline{\hat{y}} = \underline{X}\ \underline{w} \quad (14).$$

In global estimation, the following loss function is minimized:

$$I = \sum_{k=1}^{N} e_k^2 \rightarrow \min_{\underline{w}} \quad (15)$$

where $e_k = y_k - \hat{y}_k$ represent the model errors for data sample $\{u_k, y_k\}$.

The globally optimal parameters $\underline{\hat{w}}$ can be calculated either by direct methods or using iterative methods such as Conjugate Gradient method (Taner, 2001). In the direct method, (for $N>M(p+1)$)

$$\underline{\hat{w}} = \left(\underline{X}^T\ \underline{X}\right)^{-1} \underline{X}^T \underline{\hat{y}} \quad (16)$$

Results

Local Linear Modeling finds the weights relating seismic attributes to well log data. Using blind well test (cross-validation), optimum weights are found through an iterative procedure that best map log information from seismic data. Once the best weights are found, 3D volumes rock properties can be calculated from 3D seismic data. Figure (2) shows the results of blind well test for modeling a-density (with correlation coefficient of 85%), b- AI (with correlation coefficient of 87%), c- Sonic (with correlation coefficient of 84%) and d- GR log (with correlation coefficient of 73%). The modeled logs are shown in blue and the actual measured values are shown in red. Horizontal axes show the log values and vertical axes show sample number (depth).

After finding the optimal model parameters, they can be used to map rock property volumes from 3D seismic data. Some modeling results are shown in Figure (3); a) shows seismic section which was selected for modeling. It shows a section of about 250 ms length, b) shows the result of density modeling where density has been modeled for the entire seismic section and actual log measurements (at location of 50th trace where a black arrow points to the location of well) are superimposed on the modeled background. As shown in section b, our predictions in background are in an excellent agreement with the actual superimposed log measurements and high/low density layers are clearly distinguishable. Color bar shows the values of density in gr/cc. Section c) shows AI section and the measured AI is superimposed. Color bar represents AI values in units of kg/sm2. Section d) shows the modeled Gamma Ray (shaliness) values for the entire 2D section, again an excellent agreement and consistency is seen between modeled background GR values and superimposed measured GR values at well location (~ 50th trace). Color bar shows GR values in units of API.

Conclusions

A statistical method has been developed for estimation of rock properties from seismic data and tested successfully on real data sets. Unlike conventional methods that need many wells for reservoir modeling, the proposed method works with limited well log information (one well).

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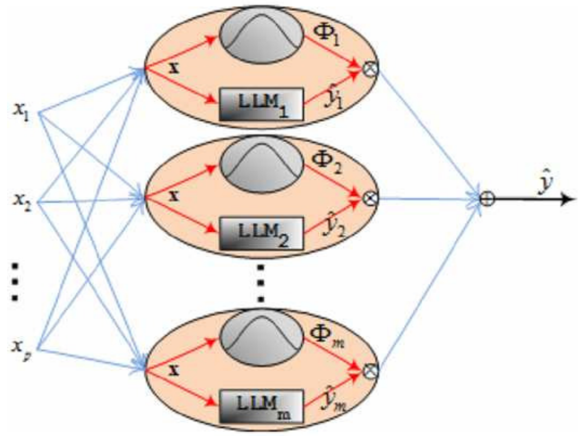

Figure. 1. Network Structure of a static local linear neuro-fuzzy model with *M* neurons for *p* inputs.(Nelles, 2001)

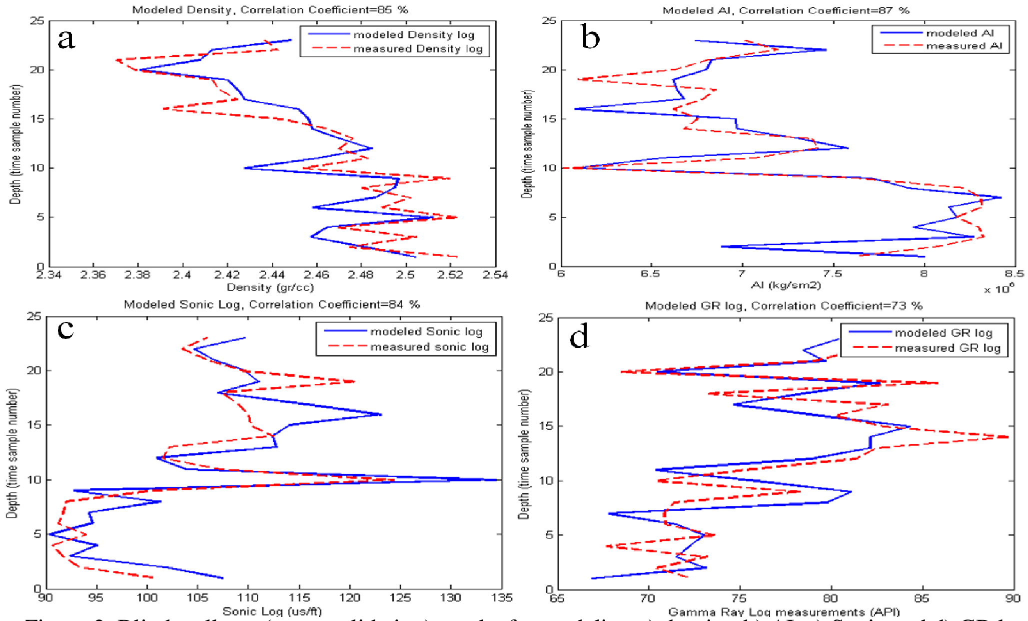

Figure 2: Blind well test (cross-validation) results for modeling a) density, b) AI, c) Sonic and d) GR log, with correlation coefficients of 85%, 87%, 84% and 73% respectively. Horizontal axes show the log values and vertical axes show sample number (time interval is about 100 ms).

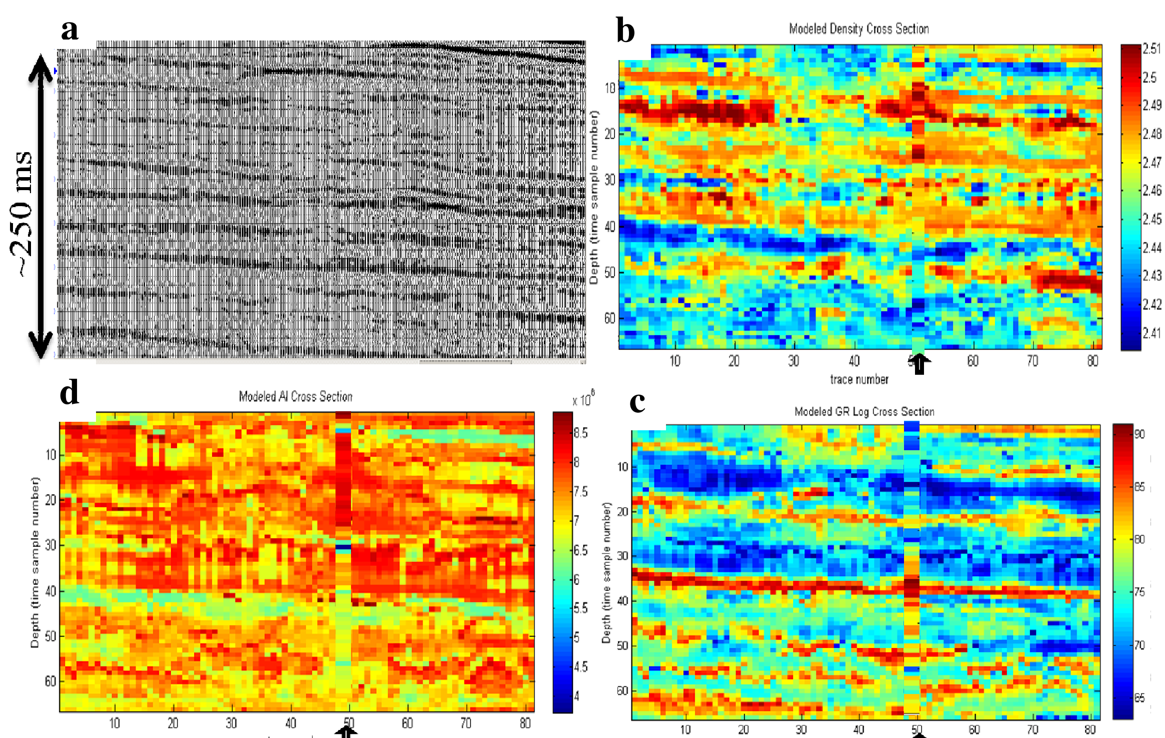

Figure 3: a) seismic section used for modeling log properties, b) modeled density log values in gr/cc units, actual measured well log values are superimposed at around 50th trace. c) Modeled AI values in units of kg/sm2. d) Modeled GR log section in units of API. More explanations are provided in the text.

EDITED REFERENCES

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