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Lithostratigraphic Interpretation of Seismic Data for Reservoir Characterization

Abstract:

Paradigm shift in hydrocarbon exploration and development strategies has increased utilization of seismic data many fold for reservoir characterization. Complicated and nonlinear relationship between seismic attributes and reservoir properties has been addressed recently using artificial neural network techniques for lithofaices classification and prediction of reservoir properties through unsupervised and supervised analysis. In lithofacies classification, analysis presumes no prior knowledge of the object to be classified and neural network looks for pattern itself. This type of analysis is very useful for areas where even no well control is available. In supervised analysis, reservoir properties are predicted away from the boreholes in inter-well regions after establishing the relation between multi-seismic attributes and well log data. In a real data example, a series of thin clastic reservoirs are sandwiched between coal and shale layers and are discrete in nature. These multi-pay sands having thickness from 2m to 8m are the main hydrocarbon producers and exhibited severe lateral lithological variation, which has affected the porosity distribution. Low porosity zones are found devoid of hydrocarbons. For better reservoir characterization, lithofacies classification and effective porosity distribution were carried out using Kohonen self organized maps(K-SOM) and probabilistic neural networks(PNN) respectively, which have demonstrated the effectiveness of these techniques. The lithofacies and effective porosity maps have provided more realistic reservoir model, which has helped in understanding the subsurface image and internal reservoir properties. The analysis has added a significant value to the exploration and development of hydrocarbons in the study area.

Introduction:

Neural networks have gained popularity in geophysics during the last decade as "An Intelligence Amplification Toolkit". In the geophysical domain, neural networks have been used for waveform recognition and first break picking, electromagnetic, magneto-telluric and seismic inversion purposes, for shear wave splitting and well log analysis, trace editing, seismic deconvolution and event classification; and many other problems (Bishop, 1999). In recent years, the unsupervised and supervised neural networks have been extensively utilized in the field of reservoir characterization and emphasis has been on integrating neural networks within a comprehensive interpretation scheme instead of as a stand-alone application. A primary attraction of neural networks is that they can be trained to give correct predictions in complicated and nonlinear cases. More recently, these neural network techniques are applied for seismic facies classification and characterization of reservoir properties. For seismic facies analysis unsupervised neural network such as Kohonen Self Organizing Maps (K-SOM) is most commonly used (Kohonen,2001). This technique does not require prior knowledge of object to be classified and is based on pattern recognition (Linari *et al*., 2003). Supervised neural networks are applied for predicting reservoir properties from the combination of various sample based seismic attributes including acoustic impedance and well log data (Hampson *et al*., 2001, Leiphart and Hart, 2001, Pramanik *et al*., 2002). In this approach, well points are considered as training points and the statistical methods are used to derive the relationships between the attributes and well log data. The technique of cross validation is used to prevent "over training". The results of training are then applied to the entire seismic volume to create a reservoir parameter volume.

In this paper, an attempt has been made to give brief description of neural networks and their application in seismic facies classification and predicting the reservoir property. In real data example, Kohonen Self Organized Maps (K-SOM) for seismic facies classification and probabilistic neural networks(PNN) to predict effective porosity distribution of reservoir sand in the study area have been applied. The seismic facies and effective porosity maps generated using artificial neural networks (K-SOM and PNN) have provided geologically more meaningful information about the lateral facies variation and effective porosity distribution.

Overview of Neural Networks:

Humans are born with large number of neurons in their brains at birth but most of the neurons are unconnected. A neuron in the brain consists of a cell body to process signals, dendrites to receive incoming electrical signals, an axon to send outgoing electrical signal, and synapses to send chemical signals to other neurons. The human brain has approximately 10^{11} neurons and 10^{14} synapses, but the number of synapses is really limitless. Once a connection between neurons is established, it is strengthened each time those neurons are activated, thereby increasing the association between the two. This process is known as "Hebbian learning" (Hebb, 1949). Different parts of the brain use different kinds of neurons and have different connection strategies depending on the function required. The process of learning and basic mechanics in an artificial neural network is similar to human brain. The computational neural network exists purely as software on a computer. A computational neural network is a mathematical algorithm, which encodes a relationship either in single data set itself or among data sets. Two main types of problems, which can be solved through artificial neural networks, are classification by unsupervised neural networks and prediction by supervised neural networks.

Unsupervised Neural Networks:

Unsupervised analysis presumes no prior knowledge of the object to be classified. The classification is purely based on the ability of the object to organize itself. This analysis is implemented by a single layer competitive network that takes the entire seismic trace in a given window as input and maps the location at which this trace was gathered into its corresponding seismic facies category. The competitive layer has a number of neurons equal to the desired number of clusters. Individual neurons are considered class representatives and they compete for each input vector during training. The neuron that resembles the input vector the most wins the competition and is rewarded by being moved closer to the input vector via the instar or Kohonen learning rules (Kohonen, 2001). Kohonen learning rule enables the weights of individual neurons to learn an input vector. Each neuron migrates progressively closer to a group of input vectors, and after some iterations, the network stabilizes, with each neuron at the center of the cluster it represents. To measure the resemblance between input vectors and each neuron, various norms can be used, such as the l_1 norm, the l_2 norm, the cross-correlation, and the semblance. The selection of the particular norm to utilize depends on which the interpreter wishes to base the analysis. For example, within the distance norms, the l_1 norm penalizes outliers to a greater extent than does the l_2 norm, and so the selection of the former would be more appropriate if numerous outliers are present in the data and suppressing them is imperative. Correlation norms are in general more sensitive to the shape of the seismic trace than the distance norms. In fact the cross-correlation is completely insensitive to the absolute amplitudes of the seismic data and depends only on the shape of the trace. Thus, distance norms are more suitable to detecting properties manifested in amplitude changes, while correlation norms are more suited to shape characteristics and are superior in detecting edge anomalies and lateral discontinuities in data. Mourice *et al.*, (1996) have given a method for using Kohonen self organizing maps (K-SOM) for automated quantitative seismic facies analysis based on the various discriminating features. This technique summarizes the seismic signature in maps and improves the precision in predicting the reservoir extent.

Supervised Neural Networks:

The objectives of these neural networks are to characterize the reservoir by identifying its parameters based on well log and seismic information. The most commonly used neural network schemes in reservoir characterization are (1) Multi-Layer Feed Forward Neural network (MLFN) similar to traditional back propagation and (2) Probabilistic Neural Network (PNN) which is analogous to kriging in geostatistics. Using neural network consists of three steps. First step is training of network in which a relation is established between data sets and learned by neural network. This is being done iteratively for the search of optimum weights using global optimization technique to each attribute for training the network. Second step is the validation of trained neural network at known well locations if they were not used during training. This process provides the confidence level about the accuracy of neural network before application. The third step is the application of trained and validated neural network on a larger volume for estimating the petrophysical properties.

Analysis window for training and application of neural network is very crucial because of two reasons (1) Training and application of neural network can be very time consuming and computer intensive if applied to the entire window. Both these functions depend on the number of samples in the training window and (2) the expected relationship may be time variant and expected to be less valid outside the training windows. These reasons suggest the application of neural network over a small window around the target zone for achieving higher accuracy.

Real Data Example:

The study area covers eastern extension of main Kalol field, Nardipur syncline and western extension of Limbodra field situated in Mehsana-Ahmedabad block of north Cambay Basin, India. Kalol Formation of Middle Eocene age is producing hydrocarbons in commercial quantity. This sedimentary section was deposited in a complex deltaic environment by distributory channels influenced by tides and also having marshy and swampy environments marked by coal, shale, sand and silt units. The sands encountered in this formation mostly represent channel mouth bars, point bars, crevasse splays etc. Kalol Formation is divided into eleven units from K-I to K-XI from top to bottom. Some of the units are again divided into smaller subunits. Multi-layered thin pay sands of K-IX unit having thickness of 2 to 8m are discrete in nature and are the main hydrocarbon reservoirs. The thickness of overlying coal varies from 13m to 32m in the study area. Due to less thickness and strati-structural hydrocarbon entrapment, systematic delineation and development of these thin clastic reservoirs is a challenging task for the explorationists.

3D seismic data covering an area of 70 square kilometers was acquired using dynamite as source. Bin size of 20mx40m was adopted for the recording of 35 fold seismic data with sampling interval of 2 msec. Standard 3D processing sequence was used to process this data volume with strict quality control. The dominant frequency of final migrated data volume is obtained in the range of 37-42Hz at the zone of interest. This migrated 3D seismic data volume along with wire line logs from 30 wells (generally including Gamma ray, resistivity, SP, neutron porosity, sonic and density) in and around the study area, geological information and testing results of the wells were used for interpretation. The steps adopted for interpretation are: log-correlation, calibration of seismic with well log data, horizons correlation, structural mapping, seismic facies analysis using unsupervised neural networks, window attributes generation, acoustic inversion and effective porosity estimation using supervised neural networks.

The sonic and density logs were available for twelve wells and were used for generating the synthetic seismograms to calibrate the geologic picks of different wells in depth to two way time of seismic data. A log correlation profile with datum at K-II top passing through wells A, B, C & D Fig.(1) clearly shows the lateral variation of individual stratigraphic sub-units of Kalol Formation. The calibration of seismic data with well logs and synthetic seismogram at well-A is shown in Fig.(2). A peak represents seismic response of K-IX coal where as composite seismic response of K-IX sands is embedded in trough just below the coal peak. Five horizons corresponding to K-top, K-III, K-VI+VII, K-IX and K-X tops were mapped.

Seismic facies analysis is carried out in two steps: first, the shape of the traces within specified interval are analyzed by a neural network which constructs a series of model traces that best represent the diversity of shapes observed through out the data set. Once these model traces are available, in the second step, each trace in the interval is compared to all model traces, and assigned to the one with which it scores the best correlation. In this example the analysis window was taken between K-IX dand K-X tops and six classes of model traces were generated. The resulting facies map(Fig.3), shows the spatial distribution of model similarity (i.e. seismic facies). It is important to note that this method does not require any well data or acoustic model. This facies map has formed the basis for subsequent analysis of the seismic interval attributes.

The attribute maps of K-IX sands have provided composite sand distribution of K-IX upper and lower sands (Fig.4). To delineate upper and lower K-IX sands, model based stratigraphic inversion was carried out combining zero phased 3D seismic data volume, well logs and interpreted horizons after proper calibration which has enhanced vertical

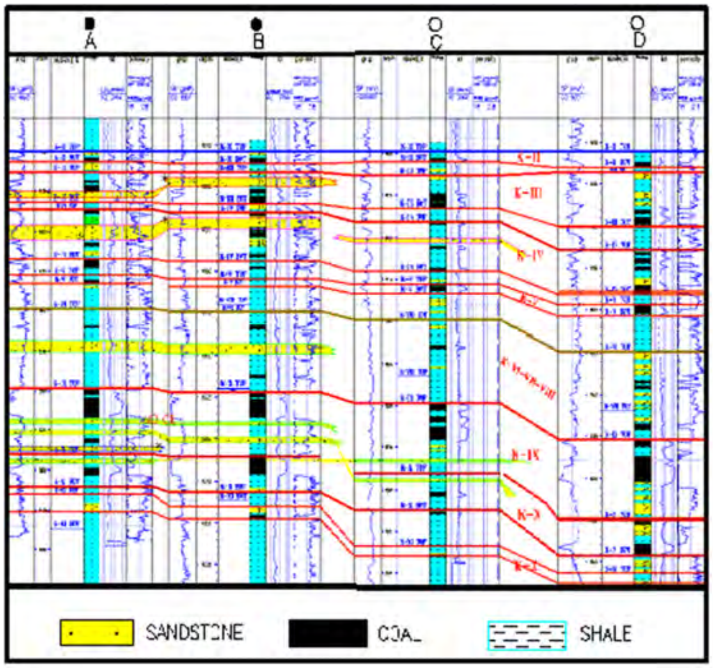

Fig-1: Log correlation profile passing through wells A, B, C & D

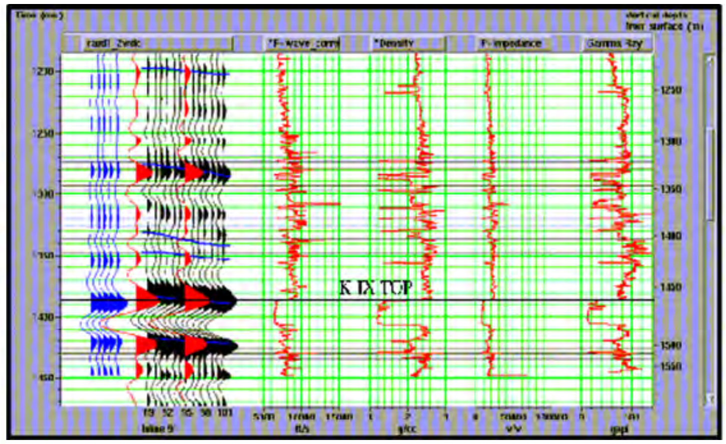

Fig-2: Well log-to- seismic tie at well A

resolution. As a result, K-IX upper and lower sands were delineated separately. An impedance map corresponding to K-IX upper sand is shown in Fig.(5) , which was generated by taking a window of 8msec. below K-IX coal base. This map shows the distribution of K-IX upper sand reservoir towards north-western part of the study area. In the eastern part, high impedance areas are due to presence of high-density silts as encountered in the drilled wells.

Effective porosity distribution was carried out using effective porosity logs, various samples based seismic attributes extracted from 3-D seismic data and inversion volume as inputs through probabilistic neural network technique. A multiattribute stepwise linear regression analysis was performed at 8 well locations using 19 attributes in the target

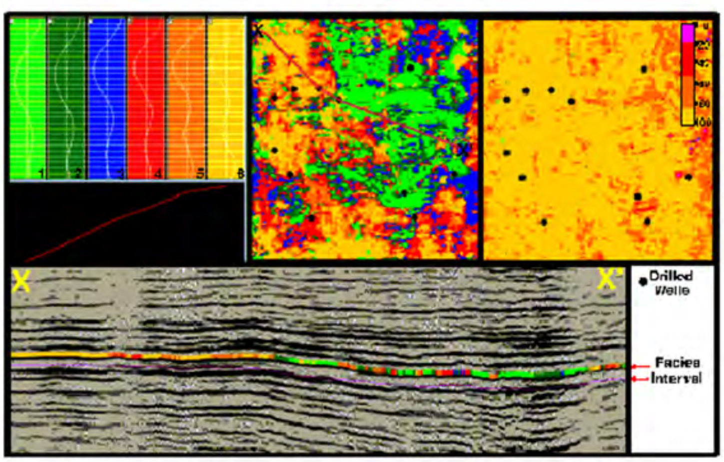

Fig-3: a) Model traces b) Seismic facies map c) Correlation map and d) Seismic section showing facies variation in selected interval

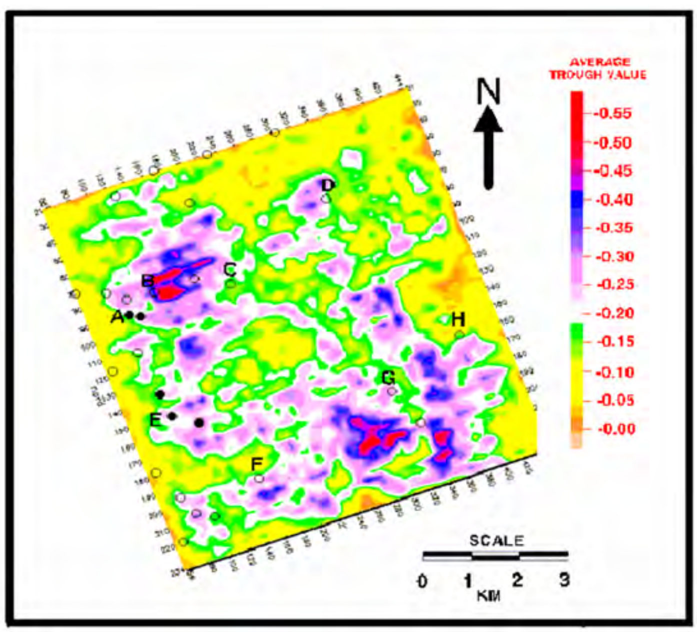

Fig-4: Amplitude map of selected interval

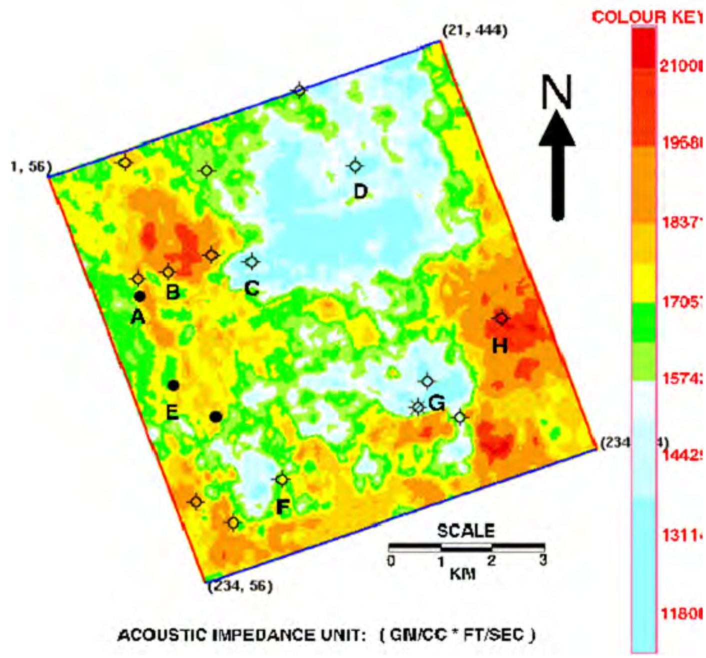

Fig-5: Impedance map of K-IX upper sand

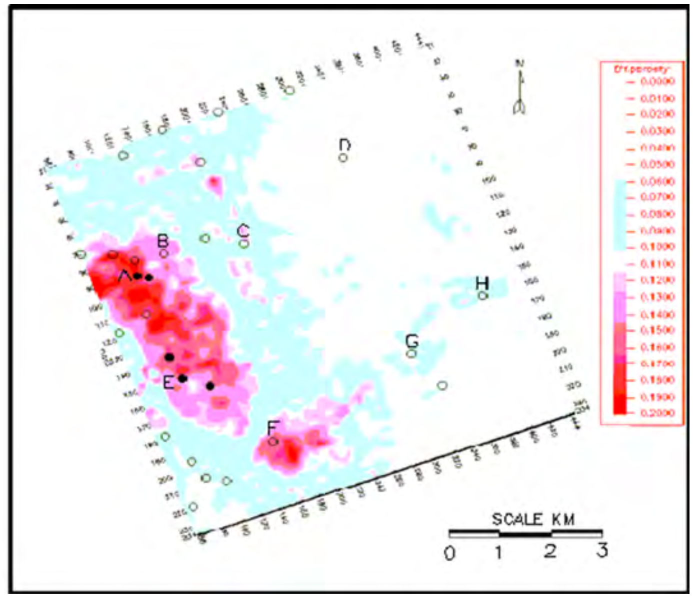

Fig-6: Effective porosity map of K-IX upper sand

window including acoustic impedance as an external attribute. A seven-point convolution operator was used. The average rms training error is computed taking all the wells into consideration. The validation error is computed by hiding one well at a time. The training error goes on reducing with increasing the number of multiattribute transforms, but validation error decrease up to 10 multiattribute transforms and increases with further increase in number of transforms. Therefore, multiattribute transforms of 10 attributes were selected to train the probabilistic neural networks. After training the probabilistic neural networks, a crossplot of predicted effective porosity values against actual porosity values using points from the analysis windows of all the 8 wells have been generated. Probabilistic neural network technique has provided correlation coefficient of 0.9287 between actual and predicted effective porosity with an average error of 2.77 percent. Predicted effective porosity logs are very close to the actual logs and the difference between them is very less in the target zone. The validation results of PNN show the cross-correlation coefficient of 0.78 with an average error of 4.7 percent PNN based prediction of effective porosity retains more of the dynamic range and high frequency content as can be clearly seen at the well locations because PNN result is a nonlinear function and closely follows the training or control data. This trained model was used to create a porosity volume from seismic data. The effective porosity map corresponding to K-IX upper sand is generated by effective porosity volume (Fig.6). The lateral effective porosity variation clearly demarcates the porous and nonporous zones in this stratigraphically controlled reservoir. The PNN result shows the lateral variability of porosity in a better way and matches the extremes of porosity. The low porosity patches between the high porosity zones are clearly demarcated.

Conclusions:

This paper clearly demonstrates the effectiveness of state-of-the-art interpretation tools developed in recent years using artificial neural network techniques. Seismic facies analysis based on unsupervised neural networks can be very useful in identification of prospective stratigraphic features in a turn-around time of days, whereas conventional approach would have taken considerably more time for a less conclusive result. This seismic facies analysis may be much useful in evaluation of large data volumes by providing at an early stage information relating to the framework of potential producing levels, validating the window based seismic attributes and acoustic inversion results and their variations, if any. Predicted effective porosity in supervised category has provided very high correlation coefficient and has greatly reduced the problem of sparse well coverage. Prediction of effective porosity distribution has provided better understanding about the quality of the reservoir. This study suggests that the ability of artificial neural networks to extract information from data and present it in a way that accentuates the features of interest allow us to make more intelligent interpretations. Thus, use of artificial neural networks can lower the risk in exploring and developing an oil field by generating final static reservoir model more coherent and reliable.

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