Multi-Attribute Seismic Analysis on AVO derived parameters - a case study

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ABSTRACT

Summary

Prospecting for reservoir zones in mature trends sometimes requires unconventional exploration tools. AVO has been successfully used as a direct hydrocarbon indicator in clastic rocks. Lately, AVO inversion for Lame parameters ($\lambda\rho$ and $\mu\rho$) has been shown to allow for enhanced identification of reservoir zones (Goodway et al, 1997). However, the overwhelming volume of data produced in AVO inversion for these parameters can make meaningful and timely interpretation a challenge. Interesting information from vertical or planar displays of these volumes singularly may not be forthcoming. In such cases, the integration of different derived AVO attribute volumes with other derived seismic attribute volumes can provide geologically meaningful estimates. This paper examines a case study wherein a probabilistic neural network solution was employed on AVO attributes derived from a 3D seismic survey acquired in southern Alberta, Canada. This information was integrated with other derived seismic attributes to develop a more comprehensive interpretation (Pruden, 2002).

Introduction

A 3D surface seismic survey was acquired over a producing Cretaceous-aged gas field in southern Alberta, with the twin objective of developing a stratigraphic model that would be consistent with the available well control and production history and also to identify locations in the area for unexploited hydrocarbon potential. The field has been producing since the early 1980s and two of the earliest, most prolific producers have begun to water out. Production is from a 'Glauconite' fluvial channel deposited within an incised valley system deposited during the Lower Cretaceous period

As the interpretive objective was stratigraphic in nature, the seismic data was processed with the objective of preserving relative amplitude relationships in the offset domain to allow for the use of AVO attribute analysis.

Time slice animation of the processed 3D migrated volume indicated the trend of the main valley cut in the northeast corner of the survey. However, as is generally the case, it was not adequate for identifying all of the channel sand features seen in the well control. Coherence Cube was considered a good candidate for this purpose. The data were datumed on an easily mapped Upper Cretaceous marker to remove the distortions of regional dip from time slices at the zone of interest. *Fig. 1(a)* shows such a datumed time slice through the coherence volume at the level of the reservoir. The definition of the main incised valley now seems quite clear.

The complex trace envelope attribute is generally used for mapping lithology changes. A composite volume containing this attribute as well as the intact coherence coefficients, is shown in *Fig.1(b)*. High envelope amplitudes were seen within the incised valley, though, while these displays were quite revealing, they do not provide information that can separate tight lithic sands from productive Glauconite sands.

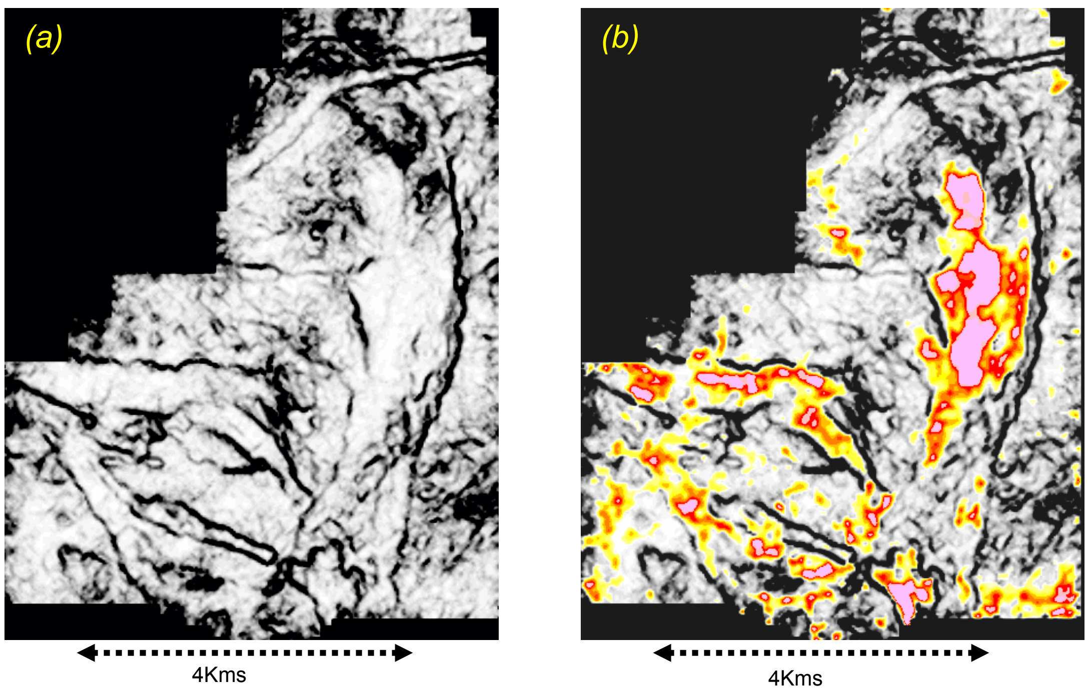

Fig. 1: Time slice flattened on the upper reference horizon through the Coherence Cube.

Because the reservoir has been depleted by gas production, high amplitude porosity anomalies will not necessarily be consistent with the presence of significant gas accumulations. Only a minor presence of gas is required within pore spaces of the reservoir rock to produce significant seismic amplitude effects (Toksöz et al, 1976). However, the fact that Glauconitic sandstone reservoir rocks can be delineated by Poisson’s ratio and acoustic impedance (Diaz et al, 2001), suggested the advantages to be gained by performing AVO inversion. The generation and calibration of synthetic seismograms with full offset stacked migrated 3D data and the resulting misties suggested the possibility of AVO effects due to lithology and pore fluid fill. Synthetic seismogram ties were compared with near offset trace stacks of the seismic volume and the full offset stack. Since the near trace stacks approximate a more normal incidence model, as assumed in the synthetic seismograms, the ties were superior. It was determined that AVO inversions for Lamé rock parameters could provide additional insight into the geologic complexity.

AVO inversion for Lamé rock parameters

Reservoir properties can be appreciated better in terms of fundamental rock parameters such as incompressibility and rigidity. Goodway et al, 1997 suggested Lambda-Mu-Rho analysis to extract lithology and pore fluid information from seismic and well log data. The basic theory for this analysis has been given in Burianyk,2000, Goodway, 2001, Ma, 2001 and Dufour et al 2002.

P-wave and S-wave impedance reflectivity responses were estimated by solving the Fatti simplification of the Zoeppritz equations (Fatti et al, 1994).

$$R = \frac{1}{2}(1 + \tan^2\theta)\frac{\Delta I_p}{I_p} - 4\left(\frac{V_s}{V_p}\right)^2 \sin^2\theta \frac{\Delta I_s}{I_s}$$

where $\frac{\Delta I_p}{I_p}$ = P-wave impedance reflectivity

$\frac{\Delta I_s}{I_s}$ = S-wave impedance reflectivity

The V_p/V_s ratio for the data was estimated from dipole sonic log data proximal to the area of study.

Impedance reflectivities are related to Lamé parameters of incompressibility (λ) and rigidity (μ) by the relationships $\lambda\rho = I_p^2 - 2I_s^2$ and $\mu\rho = I_s^2$ where ρ is bulk density.

The Lame parameters cannot be directly extracted without an estimation of the density parameter ρ.

Inversion for geological parameters

AVO inversion as described above yields several seismic attribute volumes which all contain fluid and lithological information:

Density scaled compressibility

Density scaled rigidity

Derived normal incidence P-wave stack

P impedance reflectivity

S impedance reflectivity

Fluid factor stack (Fatti et al, 1994)

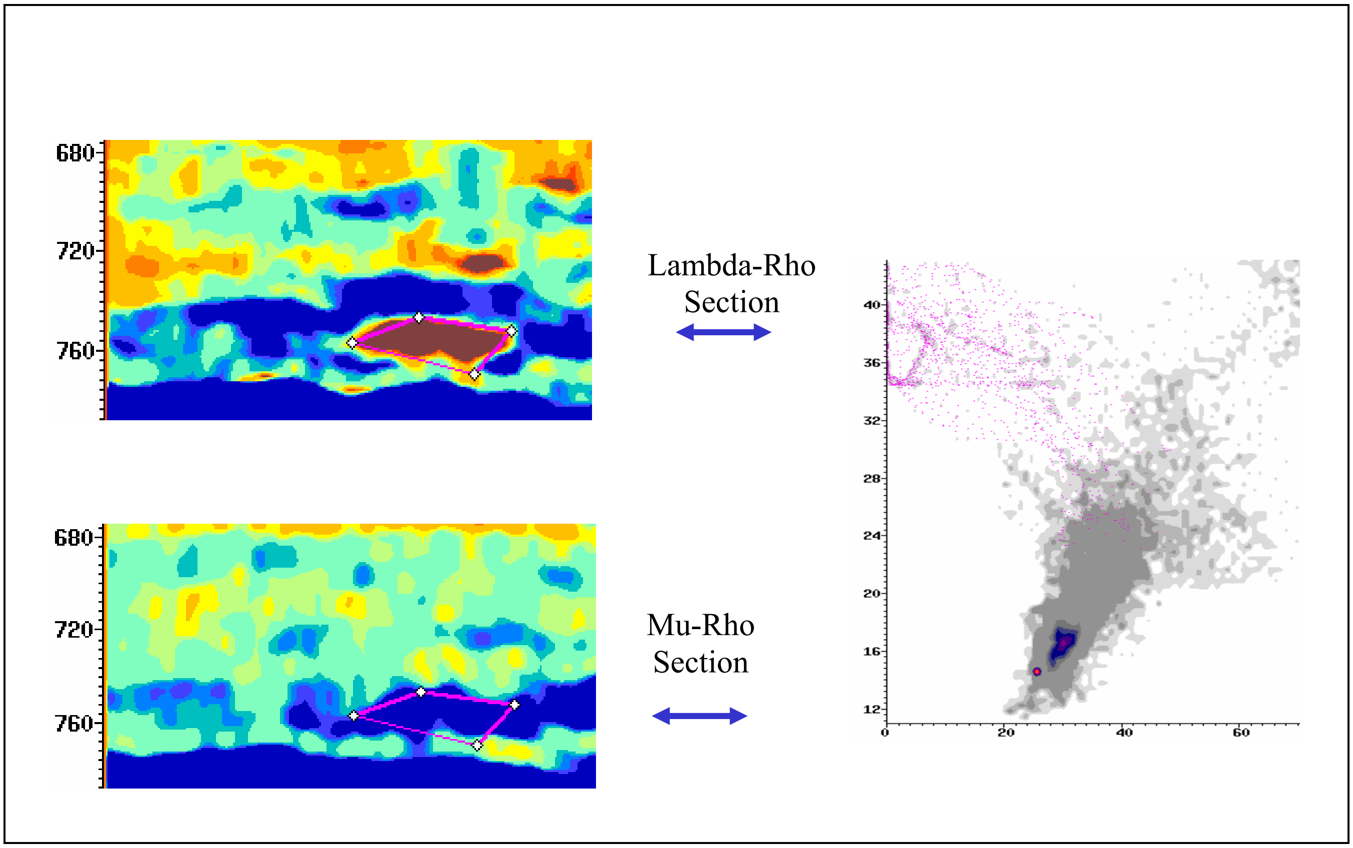

Figure 2: Segments of Lambda-Rho and Mu Rho sections and their crossplot

Fig.2 shows the Lambda-Rho and Mu-Rho sections with the anomaly enclosed in a polygon. The crossplot for these two attributes is also shown. The equivalent polygon highlights on the crossplot where we would expect the gas sands in the two dimensional space of Lambda-Rho and Mu-Rho. Additional to gas sand identification, significant lithological information is available from the data regarding the lithic and shaley sediments within the incised valley system. Determining if any of the derived volumes (variables) listed above have a connected relationship with the desired results (gas saturation and lithology) is a problem in multivariate statistical analysis.

One approach to be considered in the multivariate analysis of the derived seismic attributes involves examining the relationships between variables to see if common clusters or groupings can be formed that are particular to a given lithology or fluid fill. *Fig.2*. shows a 2 dimensional example of this approach in which gas sands tend to separate themselves in Lambda-Rho, Mu-Rho crossplot space. This approach becomes less intuitive when more than three variables are considered simultaneously. Humans cannot visualize n-dimensional crossplot space if n is greater than 4 (if color is used as a fourth dimensional separator), yet it is within this n > 4 space that clustering or separation of differing lithology and fluid fill may be most evident. An example of the separation power of cluster analysis is shown in *Fig.3*. In this example, the values for each of the 6 derived seismic attributes for each seismic trace within a window across the zone of interest have been subjected to a k-means cluster separation analysis, assuming that 4 distinct classes exist within the dataset. As can be seen in the *Fig. 3*, while the natural crossplot of Lambda-Rho and Mu-Rho across the interval studied form an indistinct cloud of values, the cluster separation has divided the data into separate zones, based on the common relationships between 6 variables, including the two posted in *Fig. 3.*

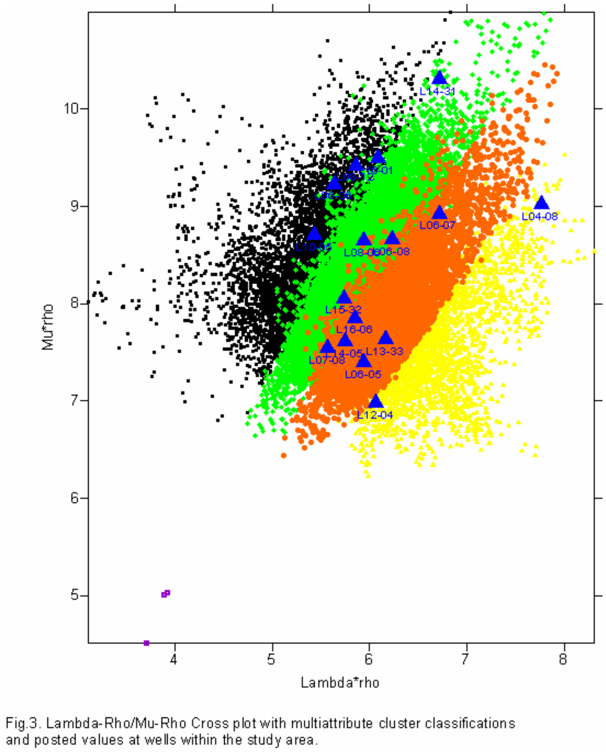

Fig.3 :Lambda-Rho/Mu-Rho crossplot with multiattribute cluster classifications and posted values at wells within the study area

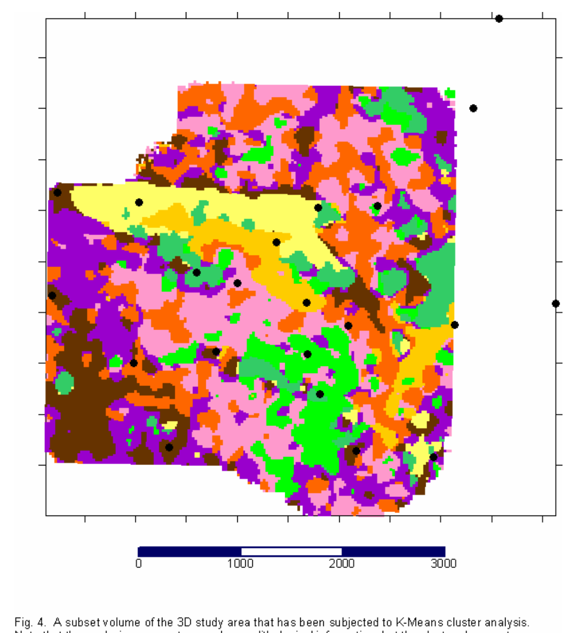

Fig.4 :A subset volume of the 3D study area that has been subjected to K-means cluster analysis. Note that the analysis appears to reveal some lithological information, but the cluster have not yet been subjected to classification according to the well control.

This type of unsupervised cluster separation analysis is often capable of creating useful character mappings of the data in 3D space by reducing a large number of attributes down to one (assigned cluster) that can be visualized on a map. *Fig.4* is a small subset of the larger 3D that has had this analysis performed. Different clusters tend to associate themselves with differing lithologies as defined in wells that sample this particular 3D space.

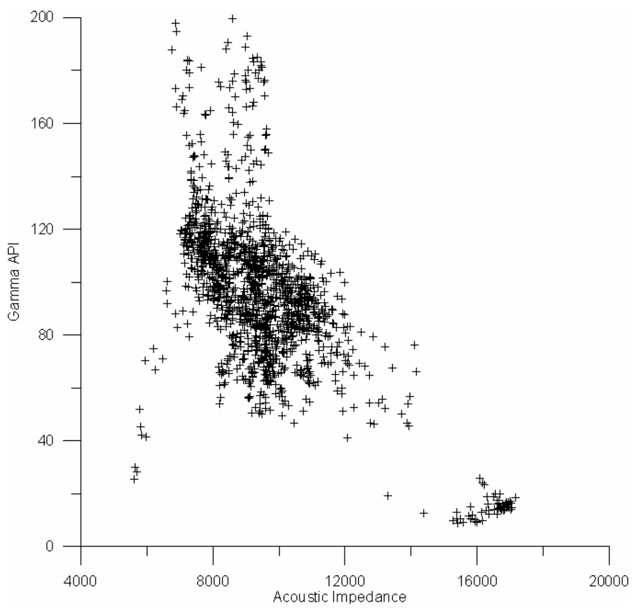

Fig.5 :Crossplot of API gamma ray values against acoustic impedance. Note the non-linear nature of the relationship.

This type of analysis has many inherent limitations: First, the number of clusters must be selected by the user and the risk exists of underestimating or overestimating the number that adequately represent the data. Additionally, there is no guarantee that the derived clusters have anything to do with the lithology or fluid fill as we wish to map it; the results are uncalibrated and unquantified with respect to the well control. Thirdly, if there is a wish to classify the data according to well control, there is no guarantee that the wells have exhaustively sampled the geological space, or that the existing well control is representative of the statistical variability of the lithology.

A more deterministic approach that allows us to be able to quantitatively relate the measured seismic attributes to a lithological or fluid indicator would be preferable. Given the well sampling within the study area and the existence of gamma ray curves for every well, it would be desirable to find a relationship between the gamma ray data and the derived attributes from seismic data. Gamma ray curves are a robust indicator of clastic rock types, used universally to separate shales from sands in log analysis. A simple analysis of the relationship of gamma ray values to acoustic impedance (*Fig. 5*) however suggests that while a general relationship between the two is visually apparent, it is clearly a nonlinear relationship. Further analysis of the other attributes with the gamma ray curve produces similar results. This leaves us with the conclusion that there is a possible deterministic multivariate relationship between the seismic attributes and gamma ray values that is nonlinear.

Nonlinear multivariate determinant analysis between the derived multiple seismic attribute volumes and the measured gamma ray values at wells is a problem that is ideally suited for neural networks (Hampson, et. al.,2001). By training a neural network with a statistically representative population of the targeted log responses and the multiple seismic attribute volumes available at each well, a nonlinear multiattribute transform can be computed to produce an inversion volume of the targeted log type.

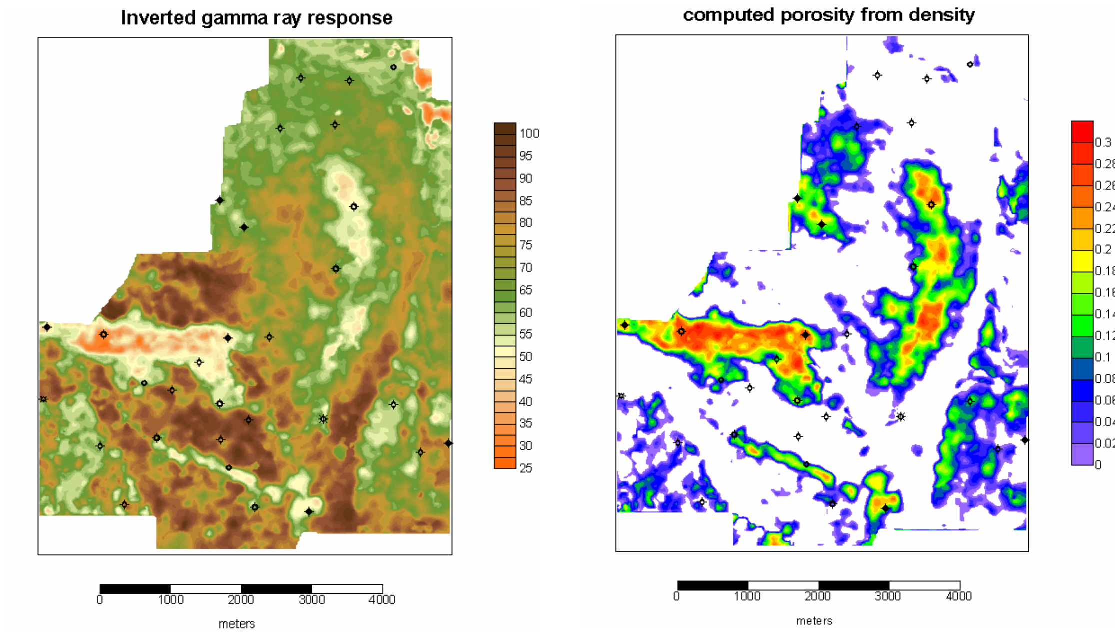

Fig. 6: Neural network inverted gamma ray response and computed porosity from inverted density response. The time slice is the same as referenced in Fig.1. Note the distinct separation of sand from silt and shale not imaged in Figure 1. The density values have been masked out for gamma ray values representative of silt or shale, giving a relative porosity indicator for the sands.

In the case of this study natural gamma ray, sonic and bulk density log curves were available over the zone of interest for sixteen wells evaluated by the 3D seismic survey. The procedure described by both Hampson et al 2001 and Leiphart and Hart 2001 was employed in this study to derive gamma ray and bulk density inversions across the 3D volume.

Discussion of results

Shown in Fig.6 is a time slice equivalent to *Fig. 1* displaying the derived gamma ray inversion, scaled to API gamma units and density inversion converted to porosity using the standard linear density relationship (Schlumberger, 1989). As is usually done, sand and silt filled channels are interpreted as having gamma values less than 50 API gamma units. This cutoff value was used to mask out inverted density values for silts and shales. A cursory glance at *Fig.6* depicts three distinct sand bearing channels. Thus, while the coherence time slice indicates the boundaries of the channels clearly, gamma ray inversion helps in interpreting major sand bodies with the channels.

The incompressibility coefficient was determined by dividing the Lambda rho value by inverted bulk density. The results are represented in *Fig.7*. Properly color coded, it is expected to represent the fluid types in an intuitive manner – high values of incompressibility (such as brine) are coloured blue, with lower (more compressible) values coloured green, suggesting oil or red, suggesting gas.

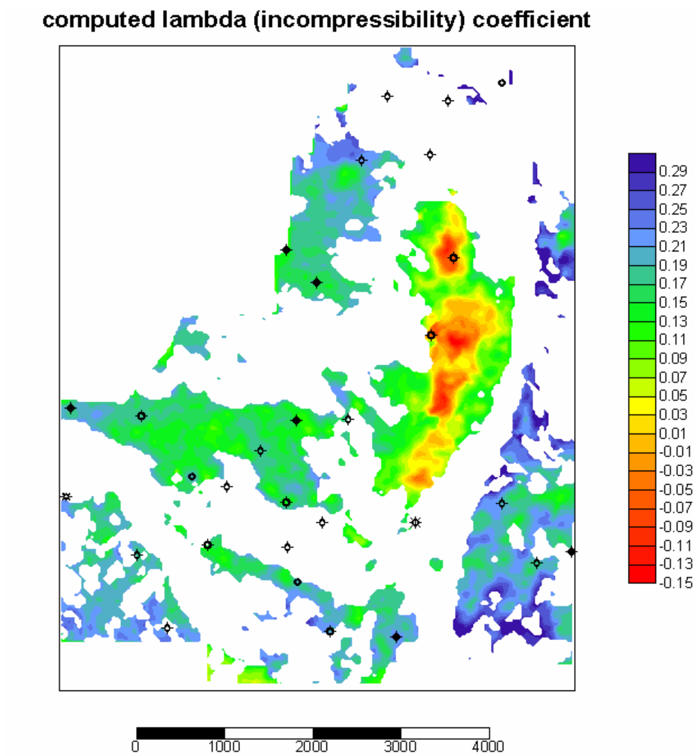

Fig.7 : Computed Lambda representing relative fluid incompressibility. High values of incompressibility such as brine, are coloured blue, while low incompressibility is represented by red and suggest gas.

Analysis of the rigidity coefficient (Mu) suggests that the sands observed within the longer, north-south trending sand body on the eastern half of the survey contains a different rock type than the sand bodies contained in the west half of the survey. These results are consistent with the observed production capabilities of the two gas wells that penetrate the north-south channel. The geomorphology of this north-south channel indicates that it was deposited in a different depositional cycle than were the other channels, providing for the potential opportunity for a different lithology to de deposited.

Conclusions

AVO inversion results for the estimation of Lame parameters were successfully integrated with other derived seismic attribute volumes using a probabilistic neural network. The resulting outputs were conventionally understood volumes of log gamma ray values and bulk dentiy. These geologically meaningful outputs contributed to the estimation of relative sand distribution, porosity and fluid content estimates.

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