Non-linearity in multi-attribute analysis – a comparative study

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Introduction

Deterministic methods have traditionally been used for prediction of reservoir properties from seismic data, wherein a relationship between observed seismic data and the reservoir parameter of interest is determined and then this transformation is used to transform seismic data to the desired reservoir property. More recently, non-linear multivariate determinant analysis using neural networks (Hampson et al 2001) between derived multiple seismic attribute volumes and the measured gamma ray values at wells have been used to produce inversion volumes of the desired log type (Pruden, 2002). Using the available gamma ray, acoustic and bulk density log curves over the zone of interest, gamma ray and bulk density inversions were derived from the 3D attribute volumes. This approach was successful, in that the two new drilling locations derived from this work encountered a new gas charged reservoir, that not only extended the life of the gas pool but added new reserves as well.

The success of this approach prompted us to try out a different method that could be used should the access to neural network software not be available. This work discusses the computation of reservoir properties using *cubic b-splines* for determination of mathematical relationships between pairs of variables derived from well logs and then transforming the 3D seismic attribute volumes into desired reservoir parameters.

Cross-plotting well log parameters

The measured well log parameters like P-velocity, S-velocity, density, porosity and gamma ray are usually crossplotted to examine the cluster patterns for different lithologies. Depending on the shape of these clisters, linear or non-linear relationships can be determined for the pair of attributes crossplotted, and then used in the transformation of seismic attributes into desired reservoir parameters. Sometimes, the shapes of the clusters or the scatter of the individual points on the crossplot make it difficult to determine a mathematical relationship in terms of its accuracy. Examples of this are the determination of a linear fit to an almost circular spread of points or a non-linear fit to an irregularly shaped cluster.

Spline curves (or mathematical representation of the approximating curves in the form of polynomials) have been used with a certain degree of accuracy depending on trade offs between drawing complexity and the generality of the curve space that they exhibit. Instead of letting the spline pass through each of the points, it is possible to specify control points on the cross-plot, based on the premise that the human eye can be relied upon to determine the desired shape of the approximating spline. B-splines are approximating spline curves with the advantage that the degree of polynomial is independent of the number of points and its shape is controlled locally in that adjusting a single point does not require total reconstruction of the curve. Of course the added computation complexity may be taken as a disadvantage. In our computation we assume that the given data are samples of a polynomial function of two variables with the samples randomly distributed in the function's domain and there is no known connectivity between the samples. A set of control points is marked on the cluster and cubic b-splines are used with a minimum of four nearest points, then shifted by one sample at a time and finally the multiple 4-point splines concatenated.

The choice of the splines's control points needs to be done carefully in that the curve through them should achieve a faithful representation of the data. Figure 1 depicts a cross-plot of P-impedance versus density for a well falling within a 3D seismic volume of the case study discussed below. Notice, the control points in red are marked first and then the spline function computed.

Case study

A case study of 3D seismic survey in southern Alberta was chosen. A neural network solution was employed on AVO attributes and the results were integrated with other seismic attributes to develop a more comprehensive interpretation (Chopra and Pruden, 2003).

The target area is a Lower Cretaceous glauconite filled fluvial channel, deposited within an incised valley system. A 3D seismic survey was acquired in order create a stratigraphic model, consistent with all available well control and matching the production history. The ultimate goal was to locate undeveloped potential within the gas sands. The field has been producing since the early 1980s and two of the earliest, most prolific producers have begun to water out.

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

Neural network analysis: Using the gamma ray, acoustic and bulk density log curves available over the zone of interest for the sixteen wells, the procedure described by both Hampson et al 2001 and Leiphart and Hart 2001 was employed to derive gamma ray and bulk density inversions across the 3D volume.

Figure 2 shows the neural network inverted gamma ray response. The sands (low gamma values) can be seen separated from the silt and shale. Similarly, the neural network generated porosity is shown in Figure 3. The higher porosity values separate the sands from silt and shale. The density values have been masked out for gamma ray values representative of silt or shale, giving a relative porosity indicator for the sands.

Cubic b-spline analysis: Figure 1 depicts a cross-plot of P-impedance versus density for a well falling within a 3D seismic volume of the case study discussed above.

A cubic b-spline curve is seen overlayed on the cluster passing through the control points (in red) marked as a guide for the best fit curve.

The crossplot for P-impedance versus gamma ray for a broad zone covering the desired sand zone shows a scatter of points is shown in figure 4. While the upper (< 70) gamma ray values can be seen to be representative of sandstone, the lower (>70) values represent the silt and shale. Consequently, the control points were marked to go through the sandstone cluster.

A crossplot of P-impedance versus porosity (Figure 5) again shows a distinct non-linear relationship and the cubic b-spline shows a reasonable fit.

The determined mathematical relationships (polynomial) for these curves was used to transform the acoustic impedance inversion volume to density, gamma ray and porosity volumes. Time slices as referenced to figure2 were displayed for each of the volumes.

Notice the close similarity between the gamma ray (Figure 7) and porosity (Figure 8) anomalous patterns corresponding to the sands. The results are encouraging especially as the mathematical relationships determined from one well has yielded results that are similar to a neural network approach followed earlier.

Composite attribute volume

Application of AVO inversion to a 3D seismic volume yields several attribute volumes that contain fluid and lithological information. It is quite overwhelming for a seismic interpreter to churn through these attribute volumes and draw his conclusions. The usual practice entails displaying each attribute volume and looking for anomalous zones and confirm their consistency in the different volumes. For example a prospective gas sand will show up low values of Lambda-Rho, high values of Mu-Rho, low values of density, high values of porosity and a suitable range of values of gamma ray.

An automated procedure was developed wherein all the five input volumes could be read in and a desired range of values specified corresponding to the gas anomalies. Figure 9 shows a time slice as referenced to figure 1. Notice the gas sand distribution matches that shown on the individual slices in figures 2-3 and 6 to 8.

Alternatively, another composite volume has been generated employing a mathematical operation that optimizes the display of the anomalous zone e.g. an operation of the form (Lambda/Mu) * (gamma ray/porosity) * density. A time slice from this volume is shown in figure 10, wherein one sees the expected pattern for prospective gas sands.

Conclusions

1. Integration of AVO inversion in terms of Lame parameters was done with seismic attributes volumes derived using cubic b-spline analysis on well log data. The results were found to be similar to an analogous integration done using neural network analysis.
2. The derived volumes, i.e. gamma ray, density and porosity contribute to the estimation of relative sand distribution and fluid content estimates.
3. A composite volume for integrating different AVO attribute volumes have been generated, that show convincing results. Use of such volumes can save seismic interpreters the drudgery of looking through individual attribute volumes.

While the above exercise has yielded convincing results, it needs to be mentioned that the results depend on the choice of clusters (e.g. gamma ray) used for the determination of the mathematical relationships. Besides, the question of whether the given well is representative of the geological space under consideration will need an affirmative answer. This approach could be difficult in areas that have a significant variability in geology in a lateral sense.

References

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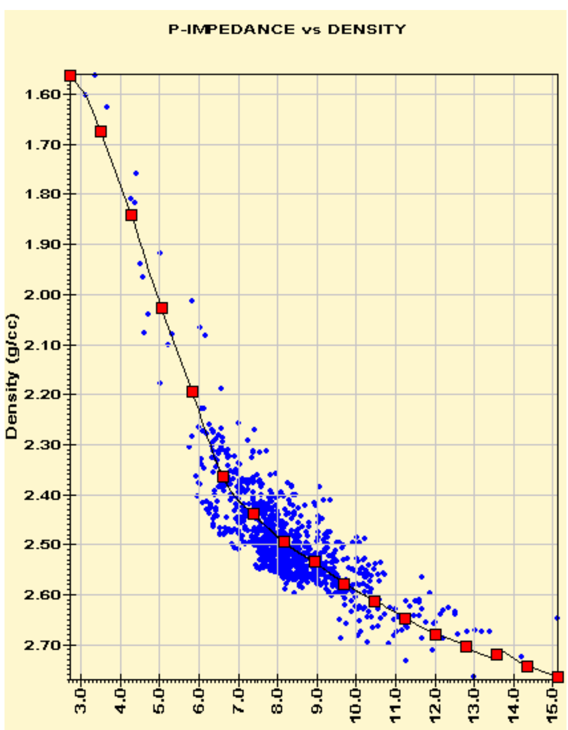

Figure 1: Crossplot of P-impedance versus density. Control points for the spline function are in red.

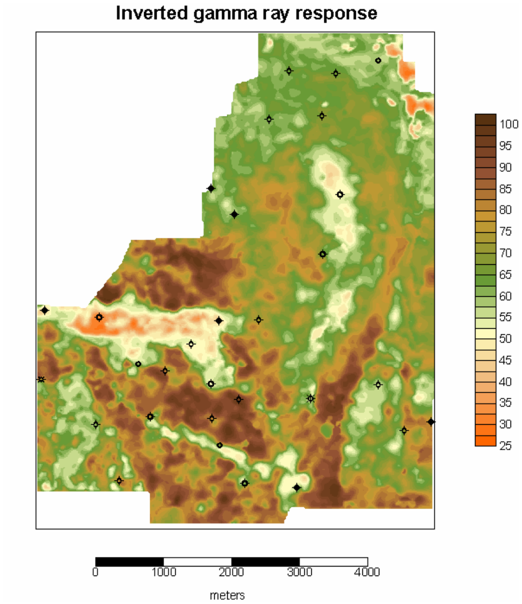

Figure 2: Neural network inverted gamma ray response. Note the distinct separation of sand from silt and shale.

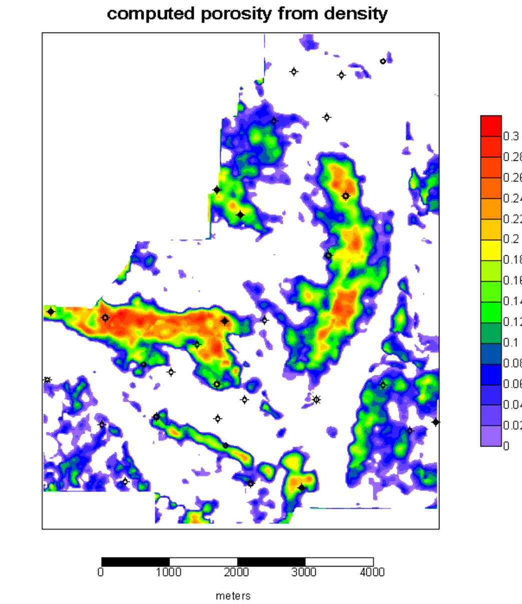

Figure 3: Neural network computed porosity from inverted density response. The density values have been masked out for gamma ray values representative of silt or shale, giving a relative porosity indicator for the sands.

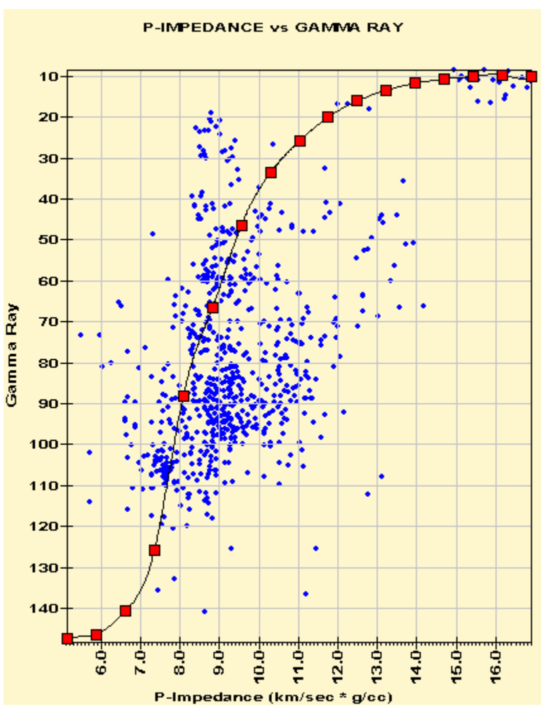

Figure 4: Crossplot of P-impedance versus gamma ray

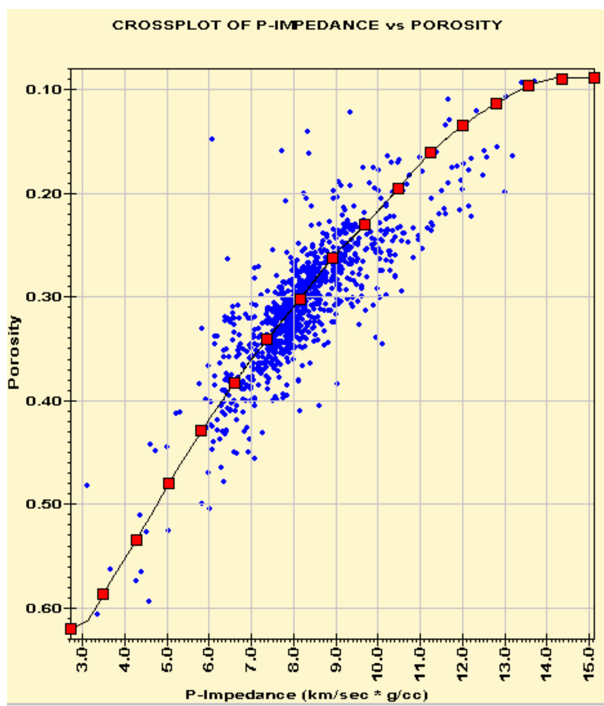

Figure 5: Crossplot of P-impedance versus porosity

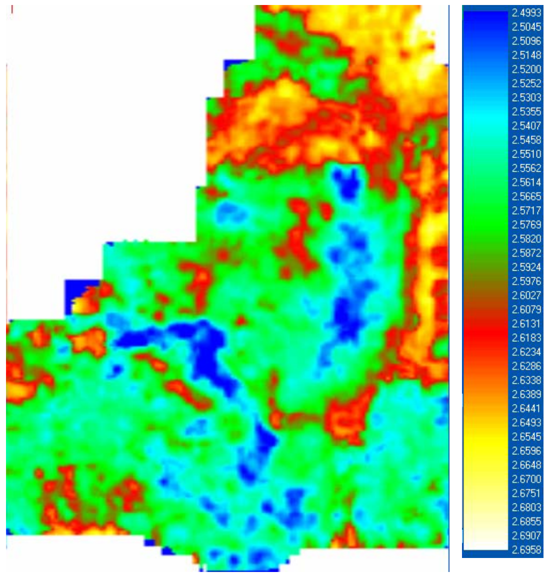

Figure 6: Spline curve inverted density. The time slice is referenced to figure 2.

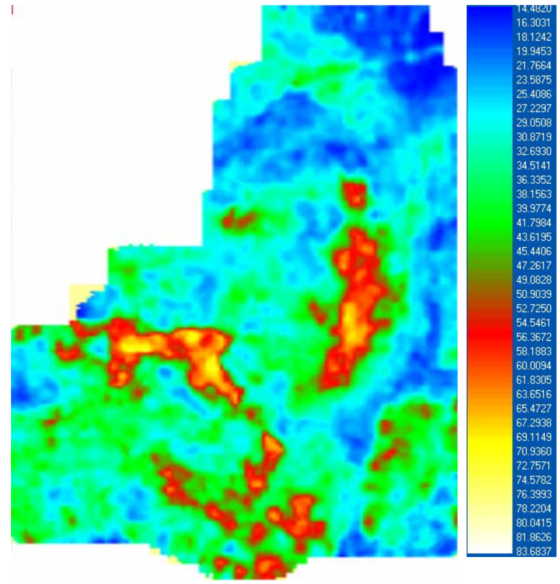

Figure 7: Spline curve inverted gamma ray. The time slice is referenced to figure 2.

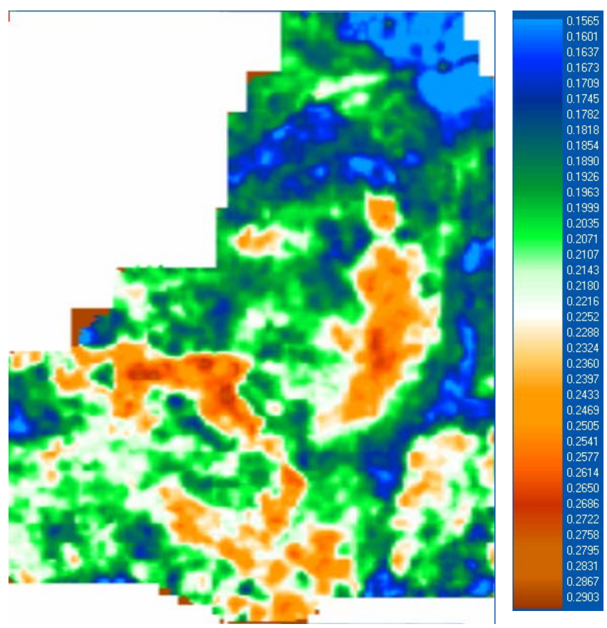

Figure 8: Spline curve inverted porosity. The time slice is referenced to figure 2.

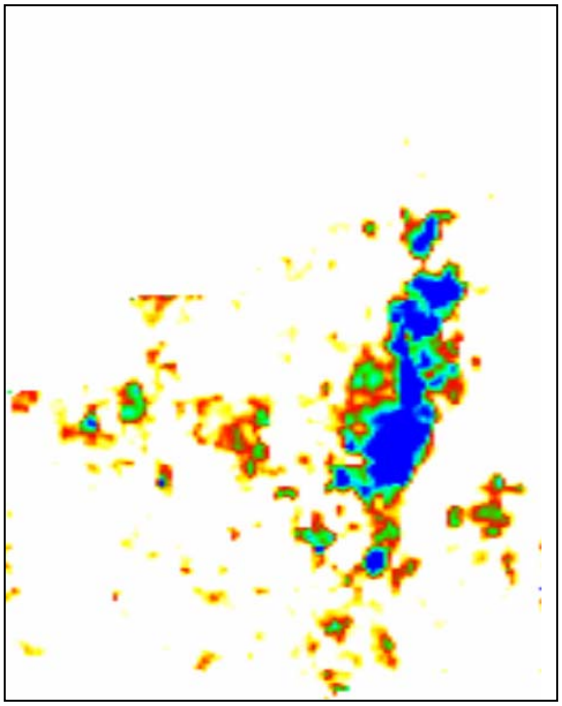

Figure 9: Time slice from composite volume with a restricted range of values for the individual attributes. The time slice is referenced to figure 2.

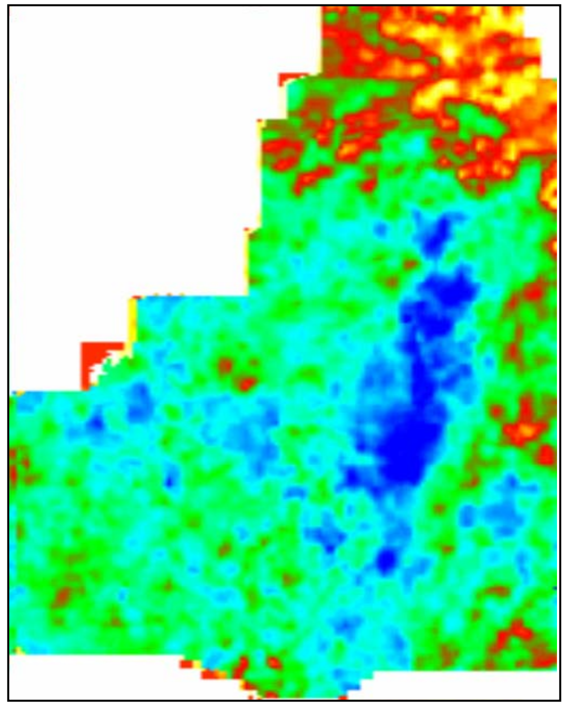

Figure 10: Time slice from composite volume optimizing the anomalous zones. The time slice is referenced to figure 2.