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Combining Geostatistics and Multiattribute Transforms – A Channel Sand Case Study

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Summary

The integration of well log and seismic data has traditionally been done using deterministic model-based approaches such as acoustic impedance inversion. More recently, statistical techniques have been applied to the problem. These approaches include geostatistical methods such as kriging with external drift (KED) and cokriging, multilinear transforms involving seismic attributes, and neural networks. In this paper, we propose a new technique that incorporates both multiattribute transforms (either linear or nonlinear) and geostatistics. We illustrate this technique with a 3D channel sand example from Alberta

Introduction

The classical problem in seismic exploration and production is how to integrate seismic data, which is spatially closely sampled but of relatively low resolution, with well log data, which is of high resolution but is poorly sampled spatially. Traditionally, this has been done using a technique called inversion, which has been well described in the literature (e.g. Lindseth, 1979). There are numerous approaches to inversion, but most assume the convolutional model, extract an estimate of the earth's reflectivity, and transform this reflectivity to impedance. Key problems that need to be overcome in inversion are the bandlimited nature of seismic data, the presence of noise, and amplitude scaling issues. Thus, the final result is an approximation to the real goal, which is a spatially extended set of seismically derived well log curves that match the measured curves at the wells themselves. One way to improve the result is to add information from other seismic attributes, such as frequency, coherency, AVO intercept and gradient, and so on. Again, this requires a physical model that relates the seismic attributes to the well log data.

An alternate approach for the integration of well log and seismic data is to use geostatistical methods such as cokriging and kriging with external drift (Doyen, 1988, Todorov et al, 1997). In this approach, the well log data is considered to be the primary dataset, and the seismic data provides a background trend. The advantage of this method is that the well ties are usually perfect, thanks to the fact that these methods honor the primary variable exactly at the well tie itself. The disadvantage is that this perfect tie often implies a less than perfect physical model. (For example, if cokriging is applied to the problem of tieing seismic structure to well derived depths, the implied velocities often show "bulls-eyes" around the well intersections.) More recently, multilinear regression and neural networks have been applied to predict well log properties from combinations of various seismic attributes (Hampson et al, 2001). In this approach, the well to seismic ties are considered to be the training points, and the statistical method being used "learns" the relationship between the attributes and the well values. The technique of cross-validation is used to prevent "over-training". The results of the training are then applied to the complete seismic volume to create a reservoir parameter volume.

In this paper, we combine the methods of geostatistics and multiattribute prediction, and show a geological application of this approach. In fact, we will actually combine all three techniques discussed in this introduction, since the key seismic attribute used in our case study turns out to be the seismic inversion attribute. Our example will involve a map-based approach, where the attributes are derived from an interval over the zone of interest of the channel sand.

Methodology

Map-based geostatistics involves the integration of two related datasets. The primary dataset is generally a set of sampled values from well logs distributed throughout the map area. These values represent some reservoir parameter of interest such as porosity or depth. The secondary dataset is derived from a separate set of measurements, generally seismic data, which is related in some way to the primary dataset. For example, seismic amplitude or inverted seismic amplitude would be expected to correlate with porosity, whereas seismic structure time should correlate with measured well depth. To test the amount of correlation between the two datasets, a crossplot can be made between them, and both the regression line and the correlation coefficient can be computed. The next step is to derive variograms from the well data and seismic data alone, and also from the well-to-seismic comparison. These variograms are then used to generate maps from the two datasets. If the well values alone are used, the technique for producing a best, linear, unbiased estimate of the unknown samples is called kriging. If we use both datasets, the techniques of kriging with external drift (KED) or cokriging can be used. The quality of the final maps can be determined either through the cross-validation technique, or a display of the error variance at each estimated point.

The multiattribute transform method involves the same input data as in the geostatistical method just described, except that multiple secondary sets of seismic measurements are used. (Actually, cokriging and KED can also accept multiple secondary datasets, but we choose not to do this here). Another key difference between this method and the geostatistical method is that, in the multiattribute transform, an exact solution is not forced at the well-to-seismic ties. Instead, a "best-fit" relationship is derived at the tie points, which is then applied to the multiple input attributes to produce the reservoir volume. Two approaches can be used to derive this relationship: multilinear regression and neural network analysis. In the multilinear regression approach, we seek a set of weights which, when applied to the attributes, will produce the reservoir volume. That is, we model the log parameter L as a weighted sum of the m attributes A_j by the linear equation

$$L(x,y) = w_0 + w_1 A_1(x,y) + \Lambda + w_m A_m(x,y) \quad (1)$$

Equation (1) differs from equation 9 in Hampson et al, 2001, in that both the estimated log values and the attributes are a function of the map coordinates x and y, rather than of time, t. Also, Hampson et al use a convolutional operator in place of a single weight value for each attribute. In the case of map data, the single weight value makes more sense.

Our second multiattribute approach involves combining the attributes in a nonlinear fashion. This can be done either by using nonlinear transforms on the attributes themselves (e.g. logarithm, square root, etc) or by applying neural network techniques. The neural network that we have found to be most effective is the probabilistic neural network, or PNN (Masters, 1995), described fully by Hampson et al, 2001. Briefly, the PNN method is like a nonlinear extension to multilinear regression, where the weights are calculated using the concept of "distance" in attribute space from a known point to an unknown point. The weighting function itself is Gaussian with an inverse scaling parameter, which can change for each of the input points.

For both the multilinear regression and PNN approaches, the number of attributes to be used is determined by a cross-validation method, in which the prediction error is computed by leaving out the target well for each of the input points and then summing the results. As we shall see in the next section, the validation error will reach a minimum at some small number of attributes, usually two or three.

Although we have described the geostatistical method before the multiattribute method, the actual order of application is the reverse of this. That is, we first use the multiattribute method to produce an improved map as the secondary attribute for the geostatistical method. We then apply the techniques of KED or cokriging to this new map. In the next section, we will apply this approach to a channel sand example from Alberta.

Case Study

Our case study involves the prediction of porosity in the Blackfoot field of central Alberta. A 3C-3D seismic survey was recorded in October 1995, with the primary target being the Glauconitic member of the Mannville group. The reservoir occurs at a depth of around 1550 m, where Glauconitic sand and shale fill valleys incised into the regional Mannville stratigraphy. The objectives of the survey were to delineate the channel and distinguish between sand-fill and shale-fill. The well log input consisted of twelve wells, each with sonic, density, and calculated porosity logs. The top and base of the sand zone for each of the wells was picked, and the porosity was averaged between the top and base as input to the mapping procedure. Figure 1 shows the distribution of wells throughout the 3D survey area.

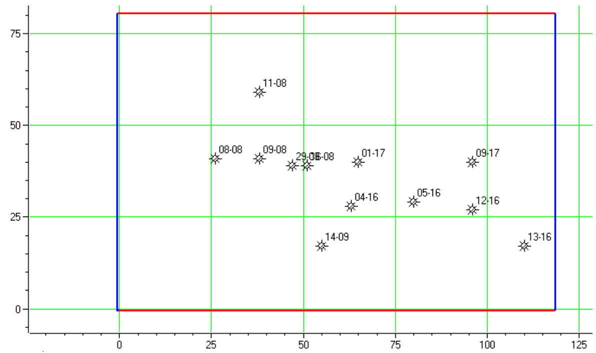

Figure 1: The distribution of the wells within the 3D seismic survey. The annotation shows inline and crossline numbers.

The seismic input consisted of two 3D volumes. The first was the stacked P-wave seismic dataset from the survey, and the second was the acoustic impedance inversion of the initial seismic volume. This inversion was done using a model-based technique that can be roughly described in two steps. First, an initial model is built from the well logs and seismic picks. Then, this model is perturbed until a best least squares fit is obtained between the model-derived synthetic seismic and the original data. Another key to this method is the extraction of a stable seismic wavelet to be used in the inversion process. Figure 2 shows the sonic and porosity logs for one of the wells in the survey, along with the seismic picks and log tops, and a portion of the seismic data at the tie point.

We then selected a series of attribute slices for the multiattribute process. The first slice was through the inverted impedance volume. The channel top was picked (this pick is shown on a piece of the seismic data in Figure 2) and then an arithmetic average from a 10 ms window below the channel top was used to produce the slice.

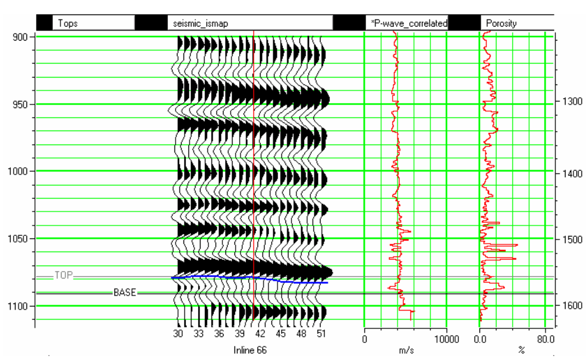

Figure 2: The well to seismic tie at one of the wells used in this study, also showing the sonic and porosity logs, and the log and seismic picks.

At the well locations, the average impedance values were then extracted from the map and crossplotted against the well porosity values. The correlation coefficient from the crossplot was equal to -0.65. The negative correlation was due to the fact that porosity varies as the inverse of impedance. The regression fit from this crossplot was then applied to the impedance slice to convert it to pseudo-porosity for display purposes. The resulting porosity slice is shown in Figure 3.

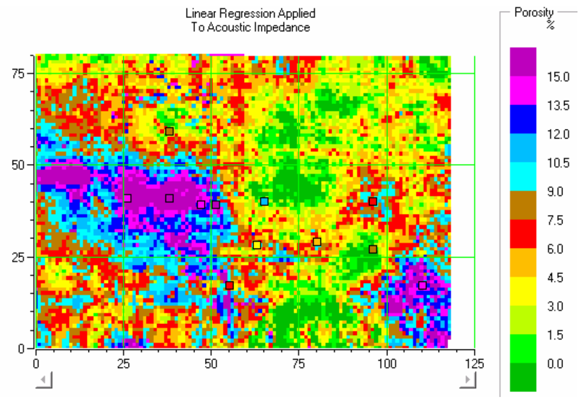

Figure 3: The dataslice from the impedance cube, averaged 10 ms below the zone of interest, and transformed to porosity.

A series of slices were then extracted from the seismic cube. These slices were also averaged over a 10 msec window below the zone of interest, using an RMS average since many of the attributes had zero mean (that is, both positive and negative values). The following six slices were extracted: seismic amplitude, amplitude envelope, instantaneous phase, cosine instantaneous phase, trace length, and integrated trace. In the case of trace length, no averaging was performed since this attribute measures the length of the trace over the zone of interest. A multiattribute analysis was then performed at the well locations using multilinear regression. It was felt that there were not enough wells to justify using the PNN algorithm. The validation results for this analysis are shown in Figure 4. Note that the top curve is the validation result, in which the target well has been left out in a jack-knife fashion.

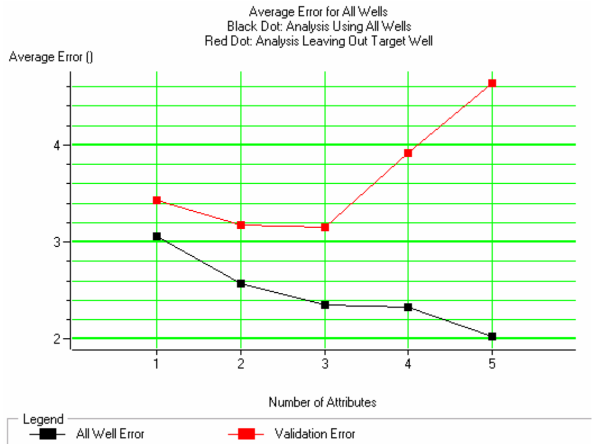

Figure 4: The average error for the best five attributes found by multilinear regression, where the top curve is the validation error found by leaving out the target well

Notice that only the first three attributes are statistically significant since the error on the top curve (which leaves out the target wells) increases after the third attribute. These three attributes were, in order, impedance, instantaneous phase, and integrated trace. The results of applying the derived weights to the attribute slices are shown in Figure 5. The correlation coefficient has now increased to 0.82.

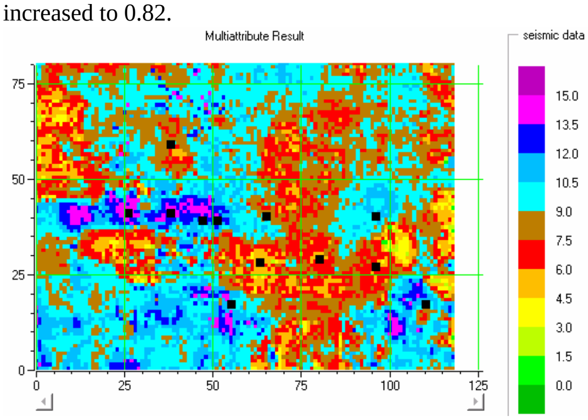

Figure 5: The dataslice resulting from the weighted sum of the first three attributes from figure 4, which were impedance, phase, and intergrated trace.

Also, note the increased resolution of the high porosity sand channel in Figure 5.

The final step in the process involves a final improvement to the multiattribute result of Figure 5, using the geostatistical technique of KED. As mentioned previously, we must first compute a variogram, and this is shown in Figure 6. In this case, we are using the Markov-Bayes linear assumption, and so we only need the seismic variogram to compute the KED result.

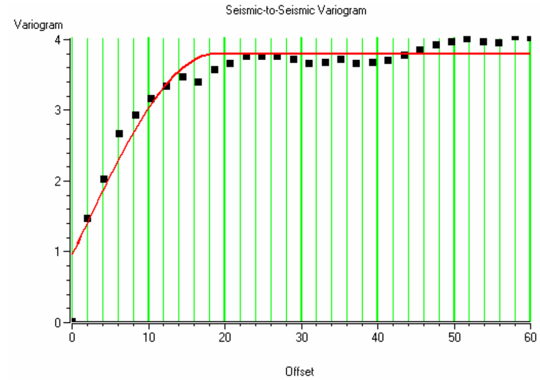

Figure 6: The seismic variogram used to produce the KED result in the next figure.

The KED porosity result is shown in Figure 7. Notice that the channel sand is now clearly delineated, and the fit to the wells is very good. This is indicated by the color within the well symbols, which has the same range as the seismic values, and is indicated by the color key on the right.

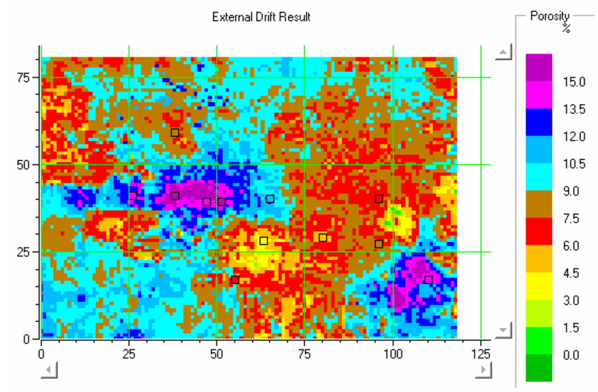

Figure 7: The result of applying the KED algorithm to the data slice of Figure 5.

Conclusions

In this paper, we have presented a new approach to the integration of well log and seismic data, which combines the methods of seismic inversion, geostatistics and multiattribute transforms. Inversion is used as the starting point, since we have found that the inversion results correlate much better with geology than the original seismic. However, by using seismic attributes in addition to the inversion attribute in the multiattribute transform, we bring in extra information that can enhance the final tie. It is also important to use the technique of validation to make sure that we are not adding spurious attributes to the final solution. Finally, geostatistics gives us a powerful set of tools for producing our final map, which combines the multiattribute transformed map with the well values, giving priority to the well information.

Our method was tested using a channel sand example from Alberta. We found that the correlation coefficient improved from 0.65 to 0.82 using the multiattribute method, and that the final KED result clearly delineated the channel sand, and provided an excellent match to the wells.

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