Seismic-guided estimation of log properties

Part 1: A data-driven interpretation methodology

By PHILIP S. SCHULTZ, SHUKI RONEN, MASAMZ HATTORI, CHIP CORBETT
Schlumberger (GeoQuest and Geco-Prakla)

Seismic data are routinely and effectively used to estimate the structure of reservoir bodies but often play no role in the essential task of estimating the spatial distribution of reservoir or rock properties. Yet, for a long time, we have been using attributes or other features of seismic data to gain useful clues in the interpretation process. Since the 1960s, we have known that reflection amplitude is sensitive to the thickness of thin beds. In the 1970s, bright spots were discovered to be useful in forecasting the presence of gas sands. Then, in the 1980s, amplitude variation with offset **(AVO)** analysis was identified as an even more refined indicator for gas sands or other situations, giving rise to Poisson's ratio contrasts. Other examples exist, such as predicting porosity from calibrated acoustic impedance values computed from seismic data.

In these methods, there is an obvious rock physics basis for anticipating the relationships that have been found. For example, dominant frequency resonance (tuning) effects are responsible for the relationship of amplitude to thin-bed thickness; impedance contrasts caused by low-impedance gas-saturated sands lead to bright spots; and velocity, density, and Poisson's ratio contrasts give rise to AVO anomalies. In each of these cases, we can start with first principles of rock physics and acoustic wave propagation and extract an approximation to relate a seismic attribute to a rock physics property (e.g., the Shuey approximation to the Zoeppritz equations for AVO, or Wyllie's time average equation approximation for porosity).

Have all the relationships been found? There may soon be another discovery of a direct and clearly derivable approximation from theory which relates a measurable seismic attribute to a rock property, but such discoveries are becoming more difficult to find. If we want additional quantitative relationships between seismic data and rock properties, we will have to change our approach.

Historically, we have identified relationships following a line of reasoning like this,

theory → approximation →‘measurement→interpretation.

We start with a theory, then make an approximation which leads to a relationship between measurable seismic quantities (attributes) and a rock property. The measurement is made on the data, and leads to the interpretation. Seismic and log data are only passive players in looking for relationships between attributes and rock properties. They may play a role only in verifying that a derived relationship works in practice.

While we know that all features of the seismic signals are directly caused by rock physics phenomena, the relationships between rock properties and the more obscure seismic attributes are not obvious. It is becoming increasingly difficult to derive attribute-property relationships directly from theory, especially those attributes which might easily be measurable on the data and which exhibit a reasonably high signal-to-noise ratio. Yet, there are many seismic attributes that we can compute, such as instantaneous frequency and reflection heterogeneity, that have no obvious relation to rock properties. Is it possible to use them quantitatively in spite of the lack of any obvious relationship to rock properties derivable from theory?

The answer seems to be yes. Specifically, in the presence of 3-D seismic data and logged wells, we have found that the simultaneous analysis of seismic attributes with borehole data often leads to better estimates of reservoir or rock property distributions, compared to estimates generated only from well data (where the seismic data are used only for geometry or structure). However, the relationships of seismic attributes to log properties are usually not obvious, and furthermore, they vary from one region to another, and even from one layer to another. Any analysis which combines seismic attributes and log properties in a quantitative way to predict property distributions must therefore include a method to identify statistically significant relationships among them.

In this article, we present and discuss the way in which we can quantitatively estimate the distribution of rock or reservoir properties using seismic attributes.

In this three-part series, we discuss a new way that 3-D seismic data are being used in the interpretation process-to help provide quantitative estimates of the spatial distribution of rock or reservoir properties, as measured from logs. Part 1 presents the methods by which 3-D seismic attributes can be usedforproperty estimation. Part 2 explains how artificial neural networks can be used to calibrate seismic attributes against properties. Finally, Part 3 will give the results of controlled studies with field data in which the resulting property maps give improved accuracy over traditional wells-only mapping methods.

Data-driven interpretation methodology. Imagine an alternative line of reasoning which starts with the data and is restricted to cases where both log and seismic data are available. Starting from the data, we accept that there may or may not be relationships inherent between seismic and log data. If they do exist,, there will be some function relating some measurable quantities in the seismic data to other quantities measured or derived from log data. Because we are taking a data-driven approach, any relationships will be, by definition, data-dependent. So, in general, we must allow that they may vary from one geologic basin to another, and even from one layer to another in the same basin (or between reservoir zones in the case of a production scenario).

If any relationships exist, we aim to find them from the data because they may not be derivable from theory in any straightforward way. One way to find potential relationships is with statistical tools. Using such tools, our data-driven interpretation scenario might look something like this:

$$\left.\begin{array}{l}\text{Seismic data} \rightarrow \text{attributes}\\ \text{Well data} \rightarrow \text{log properties}\end{array}\right\} \rightarrow \text{statistical relations+ calibration} \rightarrow \text{residual correction} \rightarrow \text{interpretation}$$

By "log properties", we mean rock or reservoir properties derived from log measurements. Let us categorize "attributes" as the result of mathematical transformations on the seismic data, prestack or poststack, but without assistance from any other type of data, such as well data. For example, log-calibrated seismic acoustic impedance sections are not attributes because logs were used in their computation. On the other hand, complex trace attributes, such as instantaneous frequency or amplitude envelope computed from the Hilbert transform, are considered seismic attributes for our purposes.

We must categorize attributes carefully because of the third step in the above process, where the log and seismic data are combined. If we are looking for statistical relations between the two data types, then we must keep them completely independent until that point; otherwise, any relationships we find will be suspect. Would you be surprised to find that a log-calibrated seismic impedance section shows good agreement with log impedance curves used in the calibration? Probably not. On the other hand, you would probably find it significant that a seismic acoustic impedance section computed without the assistance of borehole data correlates well with impedance profiles from logs. You might then have a lot of confidence that the section will be a reliable predictor of impedance values away from the well, especially if we eventually calibrate the seismic impedance with log data.

In the above interpretation flow, the relationships inherent in the data drive the interpretation. A key step, therefore, is to find which seismic attributes are related to which log properties, how reliable those relationships are, and what functional form that relationship takes.

Finding statistical correlations in the data. Before we look for statistical correlations between log and seismic data, we must make sure that the quantities we are comparing from each data type are looking at the same geologic feature or zone. In estimating spatial distributions of log properties, we normally deal with a layer rather than a horizon. Accordingly, we normally want to average both attributes (Figure 1) and log properties (Figure 2) in a vertical zone defined by two surfaces. Our immediate objective is to extract representative values of the attributes and log properties at each well that intersects the layer, so that these quantities can be crossplotted to look for relationships.

The seismic attributes normally are averaged both areally and in a vertical sense around the well intersections. The vertical averaging can be done in a layer defined by two surfaces (as in Figure 1). Alternatively, we can use a single surface and a time gate, such as 20 ms above and below the

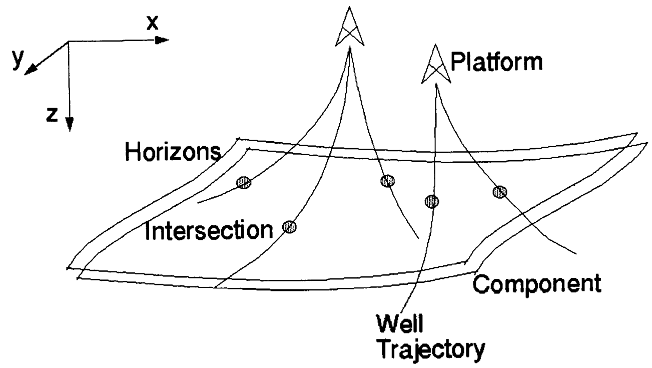

Figure 1. Attributes computed from a 3-D seismic data volume are averaged vertically in a spatially varying time zone corresponding to a geologic layer (for a thin layer, the zone is usually best specified on the wavelet). The attributes are averaged between the upper and lower surfaces of the time zone. The choice of the averaging zone can have a large influence on the attribute's significance in estimating a log property, and is a key interpretation step in its own right.

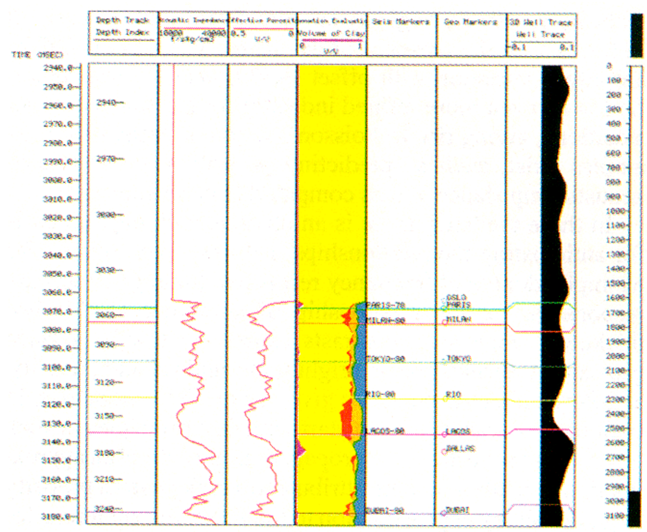

Figure 2. A single-well display of various logs and a seismic well trace extracted from an acoustic impedance volume (computed without log calibration). The seismic acoustic impedance trace shows a similarity to the log impedance and to the porosity curves, suggesting that it may have some predictive value. Log curves are averaged in a depth zone corresponding geologically to the averaging zone for the seismic attributes.

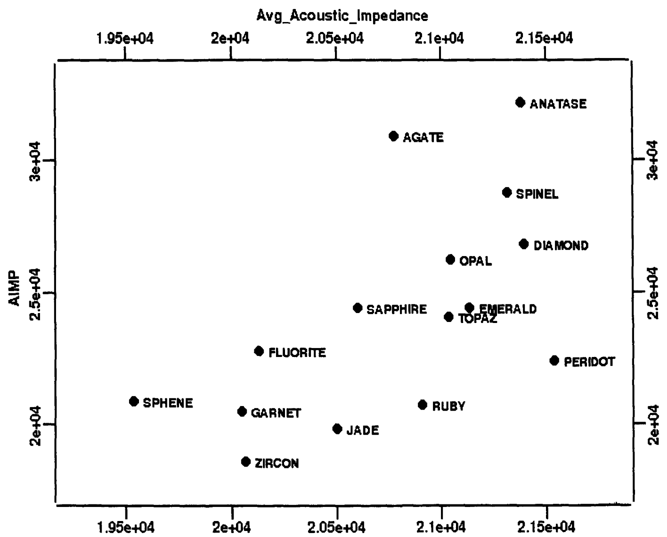

Figure 3. A crossplot of acoustic impedance from logs versus acoustic impedance from seismic for the Oslo geologic layer. Each well contributes one data point, giving an attribute value and the log property value at each well location. Although the points do not exactly fall on the line x = y, the plot shows a high enough significance (75.3 percent) that we have confidence in the seismic acoustic impedance attribute as a good predictor of the actual impedance. The well name is given next to each data point.

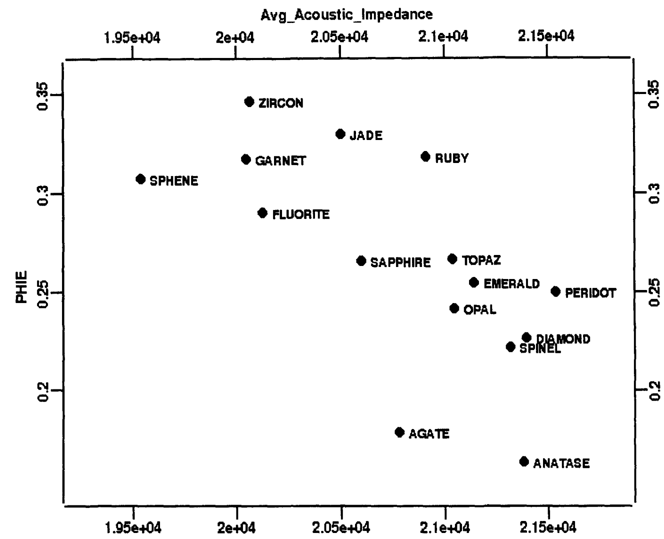

Figure 4. Log property porosity versus the seismic acoustic impedance. The trend of increasing porosity with decreasing acoustic impedance is expected from rock physics, and gives us confidence that the high statistical significance value seen here indicates a genuine relationship.

horizon. If the layer is very thin, the wavelet length on the seismic scale may be more than the layer thickness; in this case, vertical averaging of the attribute should still be done, but the zone will be controlled more by the length of the wavelet. The area1 averaging can be done within some radius of acceptance around the well intersection.

In our examples, the attributes were averaged in a zone defined by two surfaces interpreted from logs as the top and bottom of the target layer. First, log markers from multiple wells were picked. These markers were then mapped in depth, using interpreted seismic surfaces for shape control. Surfaces interpreted in this fashion are consistent with the log markers, but also reflect the structural features in the seismic. Because the layers were thin, the averaging zone of the seismic attribute was extended several tens of milliseconds below the lower surface. Time-to-depth conversion of gridded surfaces is implicit in this procedure. Area1 averaging was done using a 50 m radius.

Equally, the log values must be averaged in some fashion over a vertical interval defined by formation boundaries, which themselves may need to be edited interactively in a display similar to Figure 2. The log markers for the top and bottom surface of the layer typically are used directly to define the zone of averaging. The algorithm used for log averaging needs to be selected such that the averaged log property gives a representative value for the entire layer under consideration. Arithmetic and harmonic averaging are two such choices, and would often be chosen for porosity and permeability logs.

We do not describe these editing and averaging steps in any more detail except to point out that they are nontrivial and are important interpretation steps in their own right. Inappropriate choices for averaging zones can have a strong effect on the ability to detect functional relationships between log and seismic data.

Significance estimation and the quality matrix. At this point, we assume that attributes and log properties have been averaged over a particular vertical zone defining a layer such that each log property is represented by a single averaged value for each well, and each seismic attribute is represented by a two-dimensional grid. At each well-layer intersection point, we have a pair of values: the attribute and the property. If we have N wells that intersect the layer, then we have N attribute-property pairs that can be displayed in a crossplot.

Figure 3 shows a crossplot of the acoustic impedance computed from logs in 15 wells against the acoustic impedance computed from the seismic data without calibration from the wells. All 15 wells intersect the layer of interest, and each point in the plot represents one well. If both quantities in the plot measure the same thing, if our layer averaging was done well, and if the noise level in the data is low, all these points should lie along a straight line, but not one passing through the origin because of the lack of low frequencies in the seismic impedance. Although we can see that this is not the case, the points do tend to fall along such a distribution, giving us some confidence that this seismic attribute is to some degree successful in representing the actual trend of acoustic impedance in the layer.

How do we quantify the degree to which this scatter of points represents a significant relationship between the attribute and the property, bearing in mind that the relationship may be nonlinear? We start with Kendall's tau indicator, τ_K, which measures the degree of monotonicity of a scatter of points. If there are N points in the scatter, there is a total of $N_T = N(N-1)/2$ slopes between pairs of points. Kendall's τ_K is defined as

$$\tau_K = \frac{N_P - N_N}{\sqrt{(N_T - N_\infty) \cdot (N_T - N_Z)}}$$

where N_P, N_N, N_Z, and N_∞ are the numbers of positive, negative, zero, and infinite slopes between pairs of points. If all the slopes have the same sign, the scatter is monotonic and the absolute value of τ_K is 1. If half the slopes are positive and half are negative, τ_K will be zero. The advantage of using τ_K over other correlation measures is that it is a robust indicator of both linear and nonlinear relations. Some other statistical indicators measure only how close a relation is to being linear.

By itself τ_K is not a significance estimator. With two points,the absolute value of τ_K is 1, but there is no significance. Starting from τ_K, we want to quantify significance as the probability that these two variables are related, and we convert τ_K to a probability using the error function.

The significance is estimated from the value of τ_K and the number of points N in the scatter. We use

$$Significance = erf\left(0.477\tau_K\sqrt{\frac{9N(N-1)}{8N+20}}\right)$$

expressed as a percent, for N > 4. This gives, for example, 44 percent for $\tau_K = 0.5$ with 5 points, and 84 percent for $\tau_K = 0.2$ with 100 points. In Figure 3, the significance of the seismic acoustic impedance attribute to the impedance log property is 75.3 percent.

All attribute-property pairs can be crossplotted, their significance computed automatically, and the results summarized in a "quality matrix" table, as in Table 1. For the layer represented in the figure, called Oslo, four properties and three attributes (including the structural depth to the top of the layer) are combined to form the matrix. At a glance, we can see which attributes may be significant in predicting which property values.

Table 1. Quality matrix of attributes and log properties for Oslo layer

	Acoustic impedance	Average interval velocity	Effective porosity	Water saturation
Avg acoustic impedance	75.26	75.26	80.58	80.58
AVGV	83.63	83.63	85.01	91.51
Depth	86.30	86.30	87.51	89.66

The quantification of significance enables us to evaluate which attributes will be better than others at predicting some property. Accordingly, we would like to call up crossplots of attribute-property pairs that show relatively high significance values. We can limit the selection to those pairs that appear to be physically related. For example, in this case we looked at the acoustic impedance attribute to predict porosity (Figure 4) because theory anticipates a relationship. The crossplot shows a trend consistent with our expectation: increasing porosity corresponds to decreasing acoustic impedance. We looked also at the depth "attribute" to predict water saturation (Figure 5), because we can easily imagine a mechanism underlying that relationship.

Finally, with a crossplot editor, we would like optionally to exclude some wells because, perhaps, the log values may be questionable or the well may be in the wrong location in the formation. The next step is the determination of the calibration function.

Calibration. We want to find some function, linear or nonlinear, which will convert a set of *m* differing seismic attributes to the desired property.

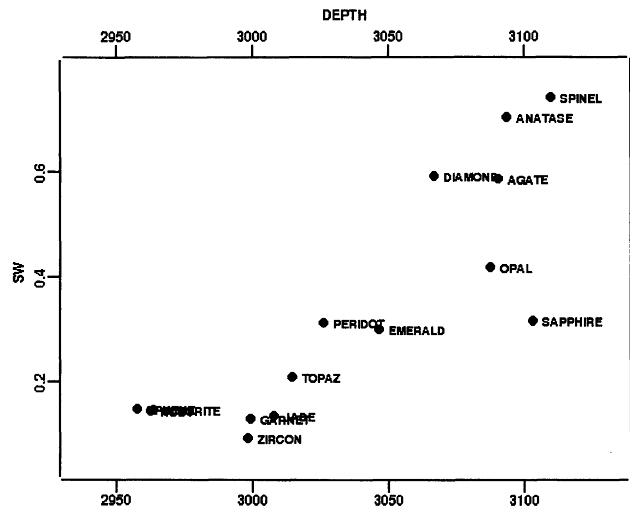

Figure 5. Crossplot for water saturation (from logs) against depth (from seismic), where depth is considered as an attribute. Since water saturation is often gravity-driven, we have confidence that the higher statistical significance here is meaningful and will be useful for prediction.

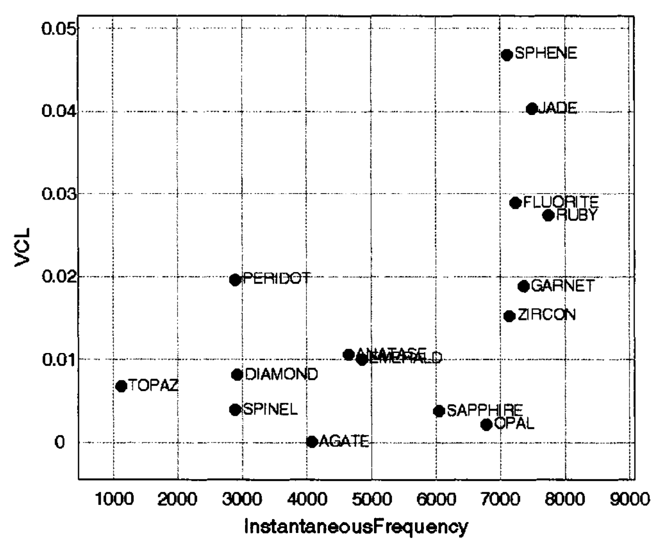

Figure 6. Instantaneous frequency attribute against the volume of clay log property for the Bravo layer, showing a significant, but highly nonlinear relationship. This plot may be showing the consequence of an increase in the number of thin shale layers causing an increase in the volume of clay on the log data and, correspondingly, giving an increase in high frequency content in the seismic. If this is indeed the underlying mechanism, there is no reason to expect this relationship to be linear.

$$Property\,(u,v) = Function(attribute_1(u,v),\ldots,attribute_m(u,v))$$

where there may be one or more attributes used to predict the porosity. (We use u,v for the two map dimensions because in Part 2 x,y will be used for input and output to the neural network.) For example,

$$Porosity(u,v) = Function(acoustic\ impedance(u,v), heterogeneity(u,v))\,.$$

In some cases a linear function will be sought. An example of a linear calibration function is

$$\Phi\,(u,v) = c_0 + c_1 Z\,(u,v) + c_2 H\,(u,v)$$

where porosity, Φ, is expressed as a linear combination of attribute grids for acoustic impedance (Z) and heterogeneity (H). The constant coefficients are found by solving a set of equations in an overdetermined system where, in general, the number of equations equals the number of wells in the learning set. Linear calibration is adequate when a relation is theoretically linear, or when the data suggest a linear relationship.

Nonlinear calibration is important when the relations are more complex. Water saturation as a function of depth sometimes shows a jump at the depth of the water cut. Also, using seismic attributes with no obvious relation to log properties may cause us to consider a more general nonlinear calibration function. For example, although instantaneous frequency is a straightforward attribute to compute, its relation to any specific log property is obscure at best. It is possible to imagine geologic settings where instantaneous frequency is influenced by the shaliness, or volume of clay, if clay layers exist in a stacked sequence.

Consider the crossplot in Figure 6, which is taken from the same data set but in a different layer, called Bravo. Here, instantaneous frequency versus volume of clay shows a 71 percent significance, but the relationship, if it is real, is obviously highly nonlinear. While we might naturally be suspicious of such an apparent relationship, it is well worth investigating since shaliness is normally very difficult to estimate from seismic data.

Table 2. Quality matrices for layers Bravo and Charlie

Bravo quality matrix				
	Vol. of clay	Vol. of dolomite	Vol. of lime	Vol. of sand
Reflection heterogeneity	13.12	66.61	24.11	34.62
Instantaneous frequency	71.19	14.50	9.40	5.65
Charlie quality matrix				
	Vol. of clay	Vol. of dolomite	Vol. of lime	Vol. of sand
Reflection heterogeneity	13.86	10.41	31.63	13.86
Instantaneous frequency	39.96	15.56	67.76	13.86

Table 2, quality matrices for layers Bravo and Charlie, shows how the attribute-property relationships can be not only subtle but also tenuous. The instantaneous frequency attribute in these two layers shows high significance for two *different* mineral volumes while showing low significance for the other. Clearly, subtle relationships between attributes and log properties will tend to be more data dependent, and we must *extract* this information from the data. Our ability to find reliable relationships driven by theory will be very limited. In any case, we need to test relationships in each data situation, as Table 2 demonstrates.

This approach is in stark contrast to the way used to estimate V_{rms}, for example, where we know *a priori* that we are going to be scanning hyperbolas in the offset domain. However, in the case of attributes, there are many possible transformations we can make on the data-some simple, some complex. The attribute in Table 2, labelled reflection heterogeneity (RH), was computed as a line integral along the curve of the trace, measuring arc length in a time zone. It shows much better significance for volume of dolomite in the Bravo layer than does instantaneous frequency, yet RH appears to be useless for predicting any log property listed in the table for the Charlie layer.

Nonlinear calibration with an artificial neural network. We now wish to determine the calibration function for a relationship showing a high significance and which appears to be nonlinear. Since nonlinear relationships are unknown and varied, instead of prescribing a particular nonlinear model to perform the calibration (e.g., a polynomial typically used in regression), we let an artificial neural network (ANN) learn a nonlinear model using example data. (ANNS will be discussed in greater detail in Part 2.)

When the calibration curve has been computed, it establishes a functional relationship to convert seismic attribute data to rock properties, but we still need a residual error correction step.

Residual correction. The calibration steps above amount to a curve fit to the points in the crossplot (Figures 4-6). In our example, there are 15 wells, giving 15 points in the crossplot. For linear relationships between a single attribute and a log property, there are two independent coefficients to be determined (from the 15 data points). Because we expect that any relationships we may discover in the crossplots will have an underlying rock physics basis, we normally try to fit a smooth curve through the points, even for nonlinear curves, which in some way might reflect that underlying, but often unspecified, physical relationship.

The natural consequence is that the calibration curve does not normally pass through all the points in the learning set. Therefore, when the attributes are converted to properties from the function implied by the curve fit, the predicted properties do not agree at the wells. There will be a residual error at each well location.

Normally, we would like our predictions either to agree exactly at the wells or for their disagreement (residual error) to be constrained within some limit. Choosing a complex calibration curve that passes through all the points will match the well data exactly, but it will almost always lead to a highly improbable functional relationship. So we prefer to use a residual correction scheme.

The correction is done first by gridding the residual errors from each well location. Then, the error grid is subtracted from the attribute-generated log property grid, which was computed using the smooth calibration function. The resulting grid gives the desired result, which is the estimate of the spatial distribution of a log property, consistent with the well data and computed from both log and seismic data.

When we require that the attribute-predicted log property estimates agree exactly at the wells, we choose the spatial interpolation (mapping scheme) so that the gridded residual errors match the actual errors at the well locations. When these two grids are subtracted, the log property distributions show exact agreement at the wells.

Occasionally, a residual error is expected to occur, due possibly to uncertainty or noise, in either or both data sets. In such a case, we wish to retain some discrepancy between the well measurements and our log property estimates at the well locations. There are several ways to retain this'discrepancy. One way is to map the error using kriging, where the nugget parameter is chosen to retain some level of discrepancy. Subtracting this error correction grid then retains the desired discrepancy. Another way is to include error bars in the log values and to define agreement as touching any part of the error bar.

The result of these two steps, calibration and residual correction, gives estimates of the spatial distribution of a log property within a layer. These estimates agree with the well measurements (perhaps with some tolerance), but they also retain both the trend and the detail of the seismic data between the wells.

Example. We took the relationship between instantaneous frequency and volume fraction of clay in Figure 6 as valid, and computed a nonlinear calibration function using artificial neural networks. Residual corrections were then applied, where we specified zero discrepancy at the well intersections. This resulted in the map agreeing exactly with the log property at the wells. Figures 7 and 8 show the results of this exercise, where the volume fraction of clay is mapped for the Bravo layer and where the colors represent the contour levels. Figure 7 shows the result of the seismic guided estimate, as described in the text, while Figure 8 gives the same map using only the log data in the estimation procedure.

We can see a much greater level of detail in the seismic guided estimates as compared to that generated from logs only. Furthermore, we expect that the seismic guided estimate gives a more accurate prediction. The estimated values between the wells for the logs-only map is specified just by a mapping algorithm. The seismic guided estimate uses one or more attributes with a high correlation to the log property being estimated to incorporate seismic guidance between the wells, followed by the residual error correction using a mapping algorithm such as that used in the wells-only survey.

However reasonable it may be to expect a better result from the seismic guided estimate, the displays of Figures 7 and 8 show only that we have increased the spatial resolution, and that both maps agree at the well intersections. They do not prove any advantage to seismic guided log property estimation. In Part 3, we will present further examples and a controlled study which will show evidence that seismic guided estimates can give significantly lower errors in predicting properties away from the wells, as compared with the logs-only estimate.

Confidence estimation. This method of attribute calibration and residual correction lets the interpreter, in principle, generate property maps using seismic attributes with little significance, with no theoretical basis in rock physics, or with erred values from incorrect horizon-well intersections. For this reason, a quantitative measure of confidence in our estimate is a useful addition to the analysis.

(Seismic-guided estimation continued on p. 315)

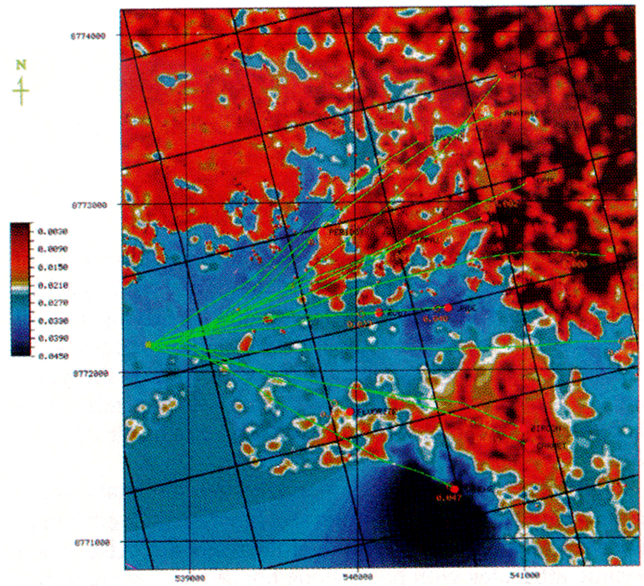

Figure 7. A basemap view, showing the spatial distribution of the volume fraction of clay, estimated for the Bravo layer. The method described in the text, seismic guided log property estimation, was employed to generate this map with instantaneous frequency as the guiding attribute. Colors represent contour levels. The 3-D seismic grid orientation is seen as the bold line grid. The fine line grid indicates UTM coordinates. The 15 wells used in the analysis (see Figure 6) are seen here originating from the same platform in a marine environment. Well TDs are indicated by red dots, while the open circles show where the wells intersect the Bravo layer. Property values are posted at the intersections. The residual correction was made with the requirement of zero error between the map and the control values.

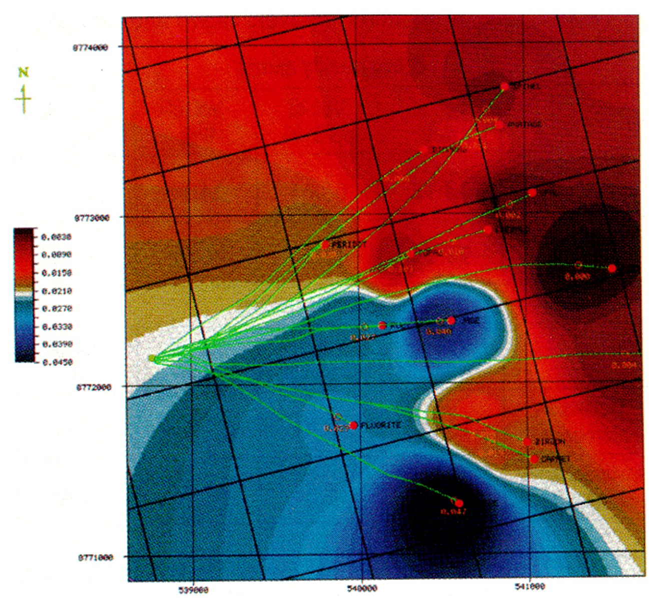

Figure 8. The same map as Figure 7, but using only log data to generate the map of volume fraction of clay. The seismic data are used here to help define the surface over which to map the property, but not to assist in the estimation of the spatial distribution of the clay fraction. Both maps agree at the well intersections, shown by the open circles and the posted values.

will still be largely absent.

Turning now to the issue of multiples in relation to stacking and deconvolution, a particularly simple means of study is at hand. We can use a vibratory or coded source and acquire data with strong signal levels at offsets approaching zero. The subsequent correlative operation to reconstruct impulsive waveforms with perhaps some simple phase correction does not involve a deconvolution process. Again, I submit that examining such data would once again find most of the theoretically predicted multiples to be absent. Obviously this approach incorporates no AVO or moveout stretch or other moveout effects.

Finally, the matter of fitting synthetics to seismic field data of any kind incorporates still other hazards. In that region of sand/shale sequences where the sands and shales "cross" in acoustic impedance (which I term sand/shale reflectivity zone II), we find many sands highly laminated with shale which are quite erratic in their seismic character as might be predicted from sonic and density logs. They are even anomalous in their electric log signatures. In fact, they constitute one of the major categories of low resistivity sands which are currently receiving much attention.

When the thickness of zone II is great (10-12 000 ft at the Texas-Louisiana border), synthetic fits are notoriously bad and resistivity derived synthetics are only slightly better. At this time, the underlying principles of what is happening here are not at all understood. For that very reason I limited the scope of discussion accompanying the conjecture. When we include this next level of geologic considerations, we must endorse John Denham's closing sentence and repeat "I have to be amazed that they (synthetics) ever fit!"

My message in terms of the conjecture remains a clearly focussed one. No matter what we do to seismic data in terms of handling, processing, display, etc. we should not lose sight of the underlying geologic information components. Mechanical considerations of our current seismic practice should not cause us to overlook serious defects in our conceptual and physical models of how our data relate to the subsurface. Hence I must thank John for raising the issues he did to help clarify our thinking and ultimately our understanding.

I also must thank an astute reader who, having great geologic expertise, recognized some errors in the diagrammatic sketch of Figure 1 accompanying my "Conjecture concerning multiple reflections." The figure showed a local area having a large influx of sediments so as to emphasize the lateral inhomogeneity of the sand development. Indeed, the sand is not even correctly positioned in relation to the slopes as it would be in the real world. Also, for this special case having such great sediment flow, the word "regressive" should be substituted for "transgressive" in the figure caption, and in the text the words "locally regressive sea" should replace "transgressive sea." The basic ideas and concepts of the conjecture remain unchanged, and I apologize to all for taking too much license with the artwork. We also thank the reader who wishes to remain anonymous for these perceptive observations. LE

(Seismic-guided estimation continued from p. 310)

Among the several ways to obtain confidence maps is the cross validation, or "leave one out" analysis. We check how closely a measured value in a well is predicted when the calibration and residual correction are done excluding data from that well. This procedure is then repeated for all wells in the learning set, and the result is mapped to give a distribution of confidence or estimated error. This measure is effective in evaluating where in the learning set do the attributes and property variables follow the general trend in the data (as seen by the calibration analysis) and where they do not. This type of confidence estimation focuses on the consistency of the well data with the attributes, and it tells us around which wells the spatial predictions tend to be more accurate.

Other measures of confidence exist, such as that obtained from multivariate geostatistical methods. Here, the value of the confidence normally decreases the farther one gets from well control, giving an indication at any point on the map of confidence in the final estimate. This type of confidence analysis results from using cokriging for the property estimation steps.

Geostatistical alternatives. Seismic guided log property estimates can also be done using a geostatistical method called cokriging, which gives an alternative to the calibration and residual correction steps. In this method, the two data sets (i.e., the well measurements and the attributes) are input simultaneously into an estimator, which uses spatial autocorrelations and cross correlations to make, in a single step, a least squares estimate of the desired property distribution, with an implicit linear calibration function (although cokriging can accommodate nonlinear functions). As mentioned above, this method also delivers a confidence map.

Cokriging provides effective tools for handling cases where the seismic data are in one or more 2-D lines, where both the attributes and the well measurements begin as scattered (as opposed to gridded) data. It can handle situations where at some spatial locations there are no data values from either data set.

With 3-D seismic data, however, the attributes are already gridded and the two-step approach of calibration and residual corrections gives some advantages-the principal one being the ability to edit manually (or even to specify) a desired calibration function, linear or nonlinear, with some rock physics relationship in mind.

Coming attractions. Part 2 will seek to provide the reader, who has no prior knowledge of the subject, a rudimentary understanding of artificial neural networks. Then we shall see, in some detail, how ANNS can be used to obtain a best-fit nonlinear calibration function for seismic attributes by "learning" from a test data set. LE