

# The generation of a rock and fluid properties volume via the integration of multiple seismic attributes and log data.

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## Abstract

We present a systematic seismic reservoir characterization workflow that integrates log and seismic data using an artificial neural network.

Seismic attributes are examined both qualitatively and quantitatively to determine the best discriminators of rock and fluid properties. These attributes are systematically classified using an artificial neural network, the Kohonen self-organizing map (K-SOM) algorithm. Ultimately, the classified litho-facies volume is calibrated to available well control by applying the K-SOM technology to well-derived data.

The product is a seismic-scale rock and fluid properties reservoir model that is consistent with borehole and surface seismic data.

The workflow is applied to the characterization of a Vicksburg-age reservoir in South Texas.

## Introduction

Seismic attributes have been used for many years as a way of qualitatively inferring rock and fluid properties from seismic data. These approaches have, in general, involved the time-consuming and laborious examination of numerous attributes in an attempt to identify elusive or misleading signatures that may be indicative of the presence of hydrocarbons, e.g. a low frequency shadow beneath the reservoir, a polarity or phase reversal at the reservoir periphery and numerous impedance and amplitude-related direct hydrocarbon indicator (DHI) effects. More recently, this process has been automated by employing a variety of artificial neural network-based classifiers. Some of these methods also use borehole data to further constrain and calibrate this classification.

For example, Russell *et al.*, (1997) describe a method for seismic analysis which makes use of artificial neural networks (ANN) to predict log-curves from multiple sets of seismic attributes. An alternative method was presented by Walls *et al.*, (1999) for training a neural network using model-driven seismic attributes, this trained network is then applied to surface seismic for lithology classification. Morice *et al.*, (1996) describe a method for using Kohonen self-organizing maps for facies analysis from seismic data.

Kohonen self-organizing maps (K-SOM) can be effective tools for defining seismic classes or facies. However, compared to other ANN-based methods, it has proven difficult to calibrate the resulting classification with borehole data.

This paper presents a new method for employing borehole data to calibrate a K-SOM data-set. The method itself is described, and a result is given for a Vicksburg-age reservoir in South Texas.

## Attribute Calculation, Classification and Calibration

The generic workflow employed in this study involved the calculation, classification and calibration of seismic attribute data. The primary elements of this workflow are depicted in Figure 1.

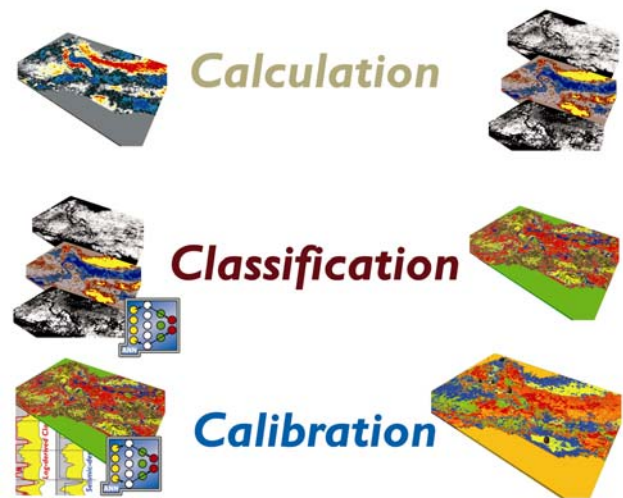


Figure 1. Workflow

## Attribute Calculation

It is possible to calculate two broad classes of seismic attributes - Physical Attributes and Geometric Attributes. In general, physical attributes respond to variations in physical properties and include Hilbert transform-derived attributes, AVO-related attributes and impedance attributes. These attributes may be computed either sample-by-sample (instantaneous physical attributes) or at the peak of the envelope (wavelet response or physical attributes). Geometric attributes, which respond to variations in reservoir morphology, e.g. structure and stratigraphy, are a manifestation of the spatial and temporal variation of physical attributes since they are computed over a user-defined time and space gate. Attributes such as coherence, semblance, similarity and other attributes designed to extract morphological elements from seismic data fall within this class.

In this workflow a suite of physical and geometric attributes is computed and visually examined to determine whether “classic” DHI’s are present and to better image fault geometries and fluvio-deltaic morphologies. Contemporary voxel-based visualization tools allow for the rapid reconnaissance of numerous attributes thereby enhancing the interpreter’s ability to conceptualize a broad spectrum of possible reservoir morphologies.

By coupling a statistical technique, such as principal component’s analysis, to the visualization process, we are

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able to determine which attributes carry the most important diagnostic weight.

Those attributes that offer the best discrimination are then classified by the K-SOM tool.

### Attribute Classification and Calibration via Kohonen Self Organizing Maps (K-SOM)

Though the classification of n-dimensional attribute data is complex in detail, the method is simple in concept.

We make two key assumptions within our workflow:

1. Borehole log-curves are analogous to seismic attributes. (Each is a representation of a sub-surface property. Borehole log-curves are formation attributes defined by the tool in use. Seismic attributes are mathematical representations of the sub-surface defined by the algorithm in use.)
2. Assuming the log and seismic data are appropriately preconditioned and of sufficient quality, we would expect both to be systematically but separately related to lithofacies.

The Kohonen algorithm is employed twice; once to classify the seismic attribute data, and once to classify the borehole information. The K-SOM method separates the well log data (density, neutron, sonic, gamma, resistivity) into 100 classes with similar log response, which implies similar petrofacies. It also separates the seismic attributes into 100 classes of similar seismic response, which implies similar lithofacies.

Core and log analysis is performed to determine the relationship between the log-derived Kohonen classes and reservoir properties. During this process, we sub-set the initial 100 classes into a reduced set of 12 “lithofacies”.

The same grouping criteria is then imposed on the time-to-depth derived seismic classes at each well. Hence we obtain a relationship between our original reservoir classes and the seismic classes. This relationship is then used to map physical properties to the seismic-derived Kohonen classes.

### Case Study

An example is given for a Vicksburg-age reservoir in South Texas.

The seismic survey covered approximately 50 square miles with 4 wells available for analysis, two of which encountered oil and saturated pay sands. The fluvio-deltaic system is located at a depth of approximately 4,200 feet and is shown in Figure 2.

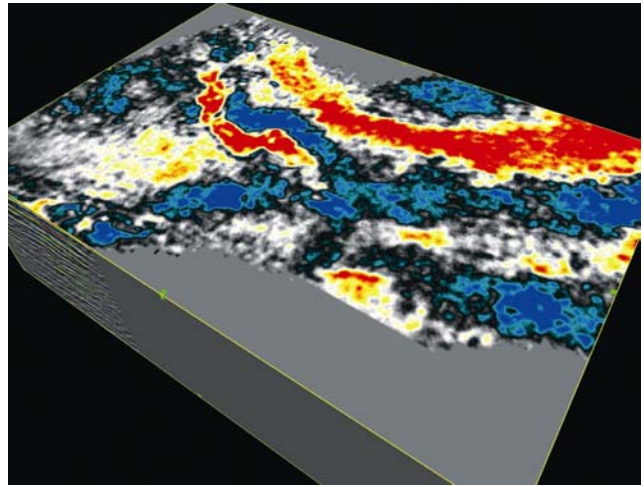


Figure 2 . Input amplitude volume at 4,200 ft.

It is well understood that no single attribute can carry enough diagnostic weight to enable discrimination between all of the features or properties of interest in the reservoir. This premise is endorsed by Figure 3 which depicts the similarity attribute.

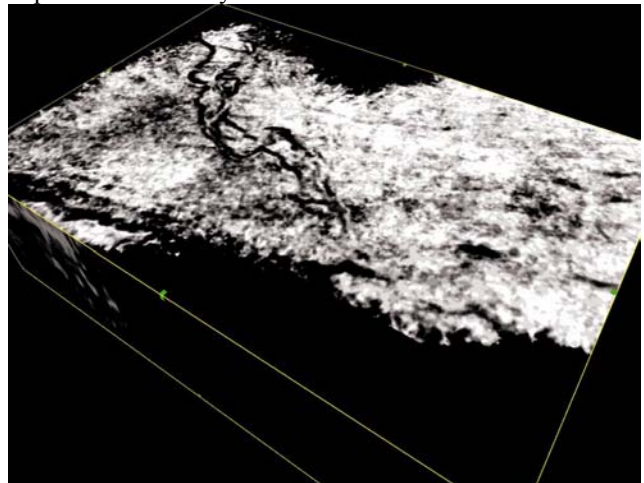


Figure 3. Similarity Attribute at 4,200 ft.

Similarity is a coherence class geometric attribute that has been engineered to emphasize the seismic geomorphology and in this example provides useful insights into the morphology of this fluvio-deltaic system.

Although the coherence class attribute enables us to make a more informed interpretation of the geometry of channeling through the Vicksburg reservoir, it tells us nothing about the physical properties in the reservoir, i.e. what’s in the channel? Is it sand or shale, what are the fluids, saturation, porosity, etc.?

To address the problem of distinguishing between sands and shales in the absence of well calibration tools, or when the impedance contrasts of the two dominant lithologies is similar, an *a priori* hybrid attribute has been developed that explicitly defines a shale based on its depositional characteristics. For example, a shale, in a clastic environment often exhibits lateral continuity, a high degree of parallel bedding and occur as thin laminae which,

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in general, cause a higher seismic spectral signature than surrounding lithologies.

The definition of a shale as having specific seismic characteristics allows for the derivation of a rule-based hybrid attribute. Therefore, a fuzzy scale of 0 to 1 can be established for values based on compliance with the declared depositional and spectral characteristics. Thus, value of 1 would represent strict compliance, and therefore be indicative of a highly shale-prone lithology whereas a value of zero would represent highly non-shale-prone lithologies. In this latter case, one might reasonably infer the presence of a sand or a carbonate. The hybrid attribute is assembled from of a suite of "physical" and "geometric" attributes that, on a sample by sample basis, analyze the seismic data for lateral continuity, parallelism (via dip-scanning) and bandwidth.

The shale indicator hybrid attribute volume is exhibited in Figure 4. In this example, the darker end of the grayscale color spectrum is more shale-prone and the lighter color is more non-shale prone. Note the possible shale-filled channel and the correlation between the lighter colors and the likely locations of point bars.

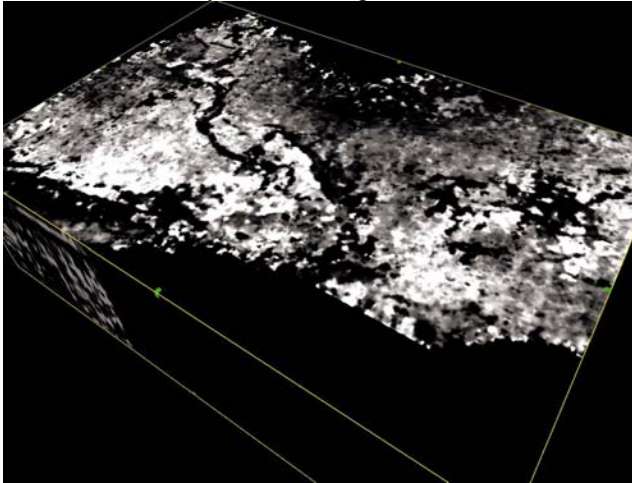


Figure 4. Shale Indicator attribute at 4,200 ft.

The shale indicator allows us to differentiate between shales and non-shales in a clastic setting. Another independently-computed seismic attribute that can also assist in this task is the relative acoustic impedance attribute. In the absence of low frequency information derived from a local well, this attribute is useful for providing insights into the variability of band-limited acoustic impedance.

In the Vicksburg example, the shales exhibit a higher acoustic impedance than the sands. The relative acoustic impedance attribute volume exhibited in Figure 5 shows a high degree of correlation between the shale-prone predictions made from the Shale Indicator attribute and the higher impedance (blue) areas in the relative acoustic impedance attribute. The lower impedances are colored yellow and it is interesting to note that these pick out possible "sweet spots" in the point bars as well as a possible deltaic facies in the south-east part of the asset.

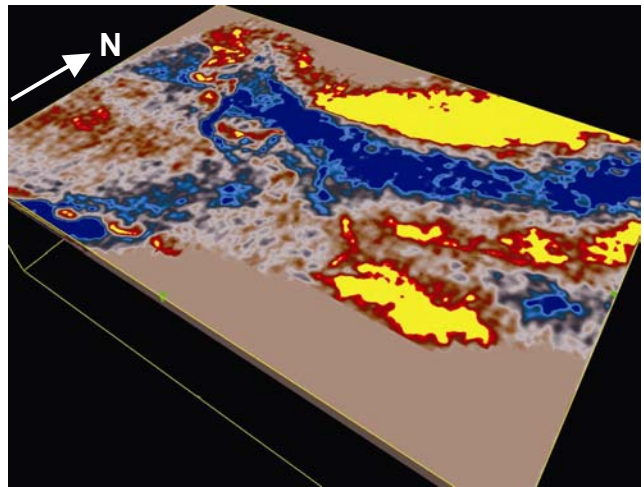


Figure 5. Relative Acoustic Impedance attribute at 4,200 ft. (low impedance is yellow, high impedance is blue).

Having identified a number of qualitatively interesting features, a suite of 8 attributes was then input to the K-SOM classifier to examine each seismic sample in a statistical sense for similarities in net multi-attribute response. Figure 6 shows the results of a classification using a 10 x 10 (100 class) Kohonen network topology.

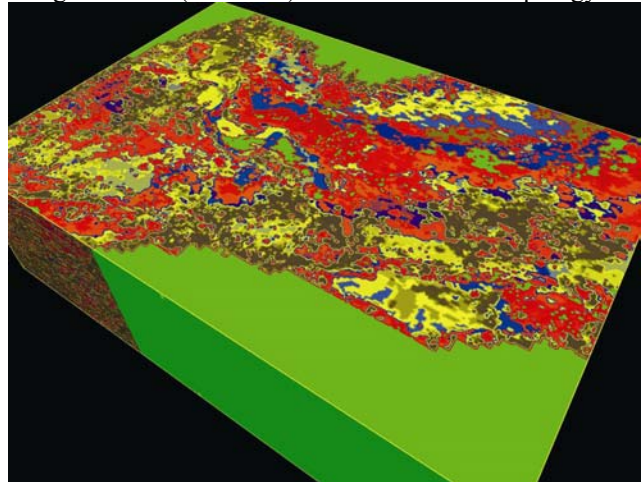


Figure 6. Kohonen (10 x 10) classification at 4,200 ft.

Note that we see a general increase in "order" within the data, and the appearance of a number of patterns with distinct geologic form. Unfortunately, as is common with this type of algorithm, it is not possible to directly infer reservoir properties from this data volume.

The same network topology was imposed on multiple log curves acquired at each of the 4 wells. The 100 log-derived Kohonen classes were then distilled down to a more manageable set of 6 classes based upon physically and acoustically relevant properties, such as acoustic impedance, Poisson's ratio, volume shale, water saturation, etc. The classes are shale, silt, 2 low quality sands, wet sand and pay sand. Figure 7 shows the Kohonen Volume after calibration using the 4 wells. The volume illustrates an additional level of order within the grouping. Furthermore, the classification is now directly related to

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specific classes of lithology, based on a log-based calibration. In this example, “yellow” represents reservoir quality sands, “blue” represents shales and “orange” poor quality silty sands.

This final classified and calibrated volume ties the available well data and clearly identifies future upside drilling potential. Figure 8 shows the tie between the seismic derived classes and log derived classes at the reservoir zone for one of the producing wells.

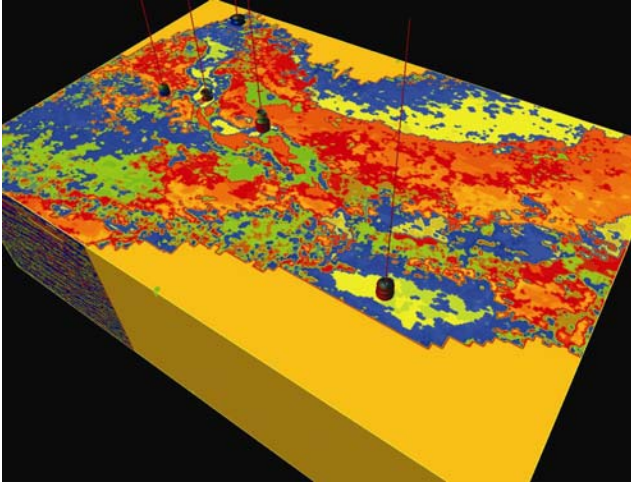


Figure 7. Calibrated Kohonen Classification

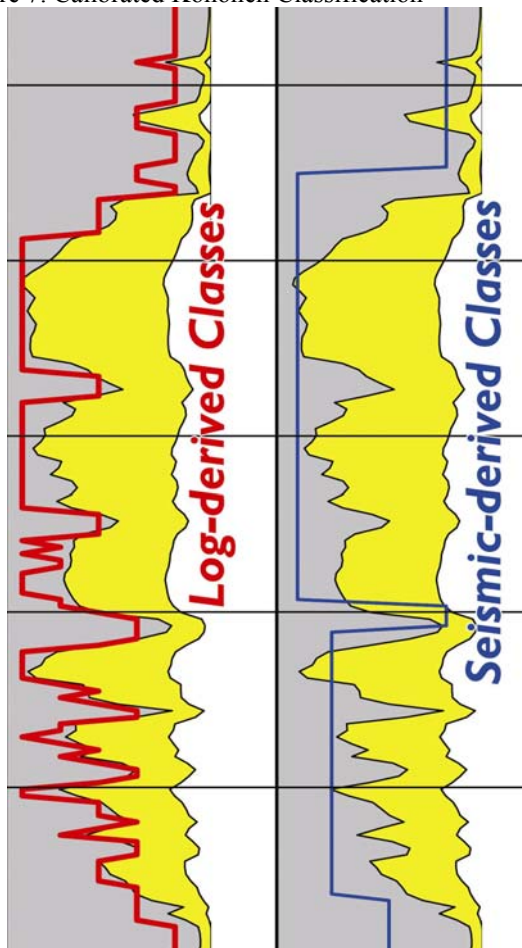


Figure 8. Log-derived Kohonen classes (left) seismic-derived Kohonen classes (right).

### Conclusion

This initial study shows much promise for the method for use in seismic reservoir characterization. The quality of the tie between the classified seismic and log-data was high. However, additional drilling would be necessary to confirm these results.

There is considerable scope for further testing and refining of this method, The flexibility of choice as regards input seismic attributes, use of pseudo-wells derived from rock-physics models and topology of the Kohonen network provides for many options for additional study.

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### Notes

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