THE AMERICAN OIL & GAS
REPORTER®
SEPTEMBER 2015
The "Better Business" Publication Serving the Exploration / Drilling / Production Industry
Reservoir Characterization

Approach Aids Multiattribute Analysis

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HOUSTON–Seismic attributes, which are any measureable properties of seismic data, aid interpreters in identifying geologic features that are not understood clearly in the original data. However, the enormous amount of information generated from seismic attributes and the difficulty in understanding how these attributes–when combined–define geology, requires another approach in the interpretation workflow.

To address these issues, "machine learning" to evaluate seismic attributes has evolved over the last few years. Machine learning uses computer algorithms that learn iteratively from the data and adapt independently to produce reliable, repeatable results. Applying current computing technology and visualization techniques, machine learning addresses two significant issues in seismic interpretation:

- The big data problem of trying to interpret dozens, if not hundreds, of volumes of data; and
- The fact that humans cannot understand the relationship of several types of data all at once.

Principal component analysis (PCA) and self-organizing maps (SOMs) are machine learning approaches that when applied to seismic multiattribute analysis are producing results that reveal geologic features not previously identified or easily interpreted. Applying principal component analysis can help interpreters identify seismic attributes that show the most variance in the data for a given geologic setting, which helps determine which attributes to use in a multiattribute analysis using self-organizing maps.

SOM analysis enables interpreters to identify the natural organizational patterns in the data from multiple seismic attributes.

Multiple-attribute analyses are beneficial when single attributes are indistinct. These natural patterns or clusters represent geologic information embedded in the data, and can help identify geologic features, geobodies, and aspects of geology that often cannot be interpreted by any other means. SOM evaluations have proven to be beneficial in essentially all geologic settings, including unconventional resource plays, moderately compacted onshore regions, and offshore unconsolidated sediments.

This indicates the appropriate seismic attributes to employ in any SOM evaluation should be based on the interpretation problem to be solved and the associated geologic setting. Applying PCA and SOM can not only identify geologic patterns not seen previously in the seismic data, it also can increase or decrease confidence in features already interpreted. In other words, this multiattribute approach pro-

TABLE 1

Seismic Attribute Categories

CATEGORY	TYPE	INTERPRETIVE USE
Instantaneous Attributes	Reflection Strength, Instantaneous Phase, Instantaneous Frequency, Quadrature, Instantaneous Q	Lithology Contrasts, Bedding Continuity, Porosity, Direct Hydrocarbon Indicators, Stratigraphy, Thickness
Geometric Attributes	Semblance and Eigen-Based Coherency/Similarity, Curvature (Maximum, Minimum, Most Positive, Most Negative, Strike, Dip)	Faults, Fractures, Folds, Anisotropy, Regional Stress Fields
Amplitude Accentuating Attributes	RMS Amplitude, Relative Acoustic Impedance, Sweetness, Average Energy	Porosity, Stratigraphic and Lithologic Variations, Direct Hydrocarbon Indicators
AVO Attributes	Intercept, Gradient, Intercept/Gradient Derivatives, Fluid Factor, Lambda-Mu-Rho, Far-Near, (Far-Near) Far	Pore Fluid, Lithology, Direct Hydrocarbon Indicators
Seismic Inversion Attributes	Colored Inversion, Sparse Spike, Elastic Impedance, Extended Elastic Impedance, Prestack Simultaneous Inversion, Stochastic Inversion	Lithology, Porosity, Fluid Effects
Spectral Decomposition	Continuous Wavelet Transform, Matching Pursuit, Exponential Pursuit	Layer Thicknesses, Stratigraphic Variations