Innovative hybrid algorithm designed to enhance seismic characterization

Pascal Klein and Andy Peloso of Paradigm present a method for multi-disciplinary interpretation of rock and fluid properties by classifying data into seismic facies volumes, used to describe and characterize seismic heterogeneities and properties.

Seismic facies analysis has been performed since the use of seismic data for E&P. The traditional method of seismic interpretation involves analyzing the seismic reflection patterns, including configurations (i.e. sigmoidal, hummocky, etc.) and their associated attributes (i.e. amplitude, frequency, continuity, etc.). These patterns and/or configurations were mapped to generate a seismic facies map. This technique, however, is painstakingly slow, very dependent on the interpreter’s skills, and limited to 2D.

With the introduction of computer-aided seismic facies techniques, this process is automated and volume-based. These techniques classify all samples from a set of seismic attribute volumes over a user specified zone to produce a volume of classified samples. The multi-attribute seismic classification methodology performs a clustering of the samples of a set of input attributes. These techniques continue to grow and play a vital role in interpretation workflows within the industry.

In recent years, there has been an explosion in the number of seismic attributes available for use in E&P. Use of these attributes helps analyze the subsurface and can reveal important features, from regional geology to detailed reservoir properties. To effectively understand the multitude of seismic attributes, Paradigm has developed classification techniques to support the quantitative assessment of exploration targets and to improve reservoir characterization within field development projects (Peloso et al., 2005). The objective of the facies classification process is to describe characteristics within the seismic data and relate these characteristics to the interpretation of rock and fluid properties and help identify quality hydrocarbon accumulations.

Technology

Clustering algorithms are more or less adapted to the management of a large number of objects. The K-means algorithm offers undeniable advantages because it enables the interpreter to perform seismic clustering on a large volume of data at low cost. The drawback, however, is that it produces a fixed set of clusters based on the initial center positions. On the contrary, Hierarchical Clustering is a family of algorithms that can be qualified ‘deterministic’, generating the same results using the same data. Moreover, these algorithms provide hints on the number of clusters to use, but are badly adapted to huge data sets. In fact, the K-means algorithm is actually a complement to other clustering techniques. While providing clustering of large data sets, it enables the reduction of the data set size, by carrying out prior groupings. For these reasons, the hybrid algorithm was developed to adapt to the clustering of large volumes of data consisting of thousands or tens of thousands of objects. This innovative approach is the combination of two clustering techniques and is appropriately named Hybrid Clustering (Wong, 1982).

Hybrid Clustering (Figure 1) is performed in three phases. 1) Initial separated where the dataset to be clustered is initially partitioned in order to obtain tens, even hundreds of prototype vectors that optimally represent the original dataset, but with a smaller number of objects. Utilizing the K-means algorithm (Figure 3), the separation increases between groups for each iteration, which generates a partition of a fixed number of prototype vectors, depending on the initial choice of centre positions. These prototype vectors become the basic elements of the next phase; 2) Hierarchical aggregation. The objective of this step is to reconstitute clusters which have been fragmented and aggregate objects around their original centers. Ascendant Hierarchical Clustering of these prototype vec-
tors is performed with the final number of cluster centres being given or suggested by the dendogram (Figure 2); and 3) A tuning phase is performed, one more time, using the K-means algorithm. This optimization consists in slightly adjusting the cluster centres so that they optimally represent the objects of the original dataset.

The advantages in using this hybrid technique are two fold:
1. The partitioning phase has been designed to remove the noise contained in the original data. The prototype vectors identified during this phase hide the noise from the subsequent Hierarchical Clustering, the latter having proved to behave far better in such optimized conditions and produce less non-specific clusters.
2. The reduction of the number of objects during the Hierarchical Clustering phase has a significant impact on the memory requirements and computational time, making the Hybrid Clustering technique very attractive for large volumes of data.

Case studies
One typical workflow normally begins with well data analysis, if available, and interval definition for the seismic facies classification process. Calibration of the well data to the seismic data is a key component of the workflow and is vital to the quantification of the facies results. Fluid substitution and modelling utilizing crossplot analysis are used iteratively to help analyze the resultant facies volumes. Figures 4 and 5 depict results from a case study utilizing data from the LaPalma field published in The Leading Edge (Linari et al., 2002). This field lies within the Colon Unit oil province (southwest corner of the Maracaibo Basin) in Venezuela. Figure 4 shows two crossplots of AVO attributes (Fluid Factor and P-impedance reflectivity) post classification. The left crossplot depicts conventional clustering and the right, Hybrid Clustering. Notice how the data clusters and their corresponding centres appear to more effectively describe the data with hybrid versus conventional clustering. Based on the well information, the wet and oil sands were assigned different seismic facies classes.

Figure 5 shows traditional clustering on the left juxtaposed to a comparable horizon slice from the hybrid facies volume. The traditional unsupervised clustering fails to show any differentiation between the wet (white) and oil wells (green). The Hybrid Clustering has assigned different seismic facies classes for these wells. Note the NE-SW trend (brown facies) was penetrated by the producing wells and interpreted as an oil-bearing sandbar.

Another example of the effectiveness of Hybrid Clustering is from a carbonate study. The objective of this project was to delineate the facies distribution and predict the fluid and porosity content of this carbonate formation based on the integration of information from multiple elastic attributes (AVO, Lambda-rho, Mu-rho) and well data. Based on the well modelling, Lambda-rho, Mu-rho were sensitive to changes in porosity in the carbonate formation. By classifying these attributes using the Hybrid Algorithm, Paradigm was able to identify and predict porous zones in the carbonate formation (Figure 6). The interpreted porous zones are in red within the limestone, while increase of porosity in the richer dolomite formation has been assigned blue/green facies. The producing wells are in black and the dry wells are in blue. The producing wells (black) in the hybrid facies volume (Figure 7) all appear to fall within the interpreted red facies (porous) pattern. The exception is the producing well to the west (green facies) which has been interpreted as more dolomitic. The conventional facies volume to the right does not discriminate between the producing and wet wells and is much more difficult to interpret.
Figure 4 Crossplot of Fluid Factor and P-Impedance reflectivity. The rectangles represent the centers of the clusters which are color-coded and assigned a class number.

Figure 5 Horizon slices from facies volumes using conventional clustering on the left and hybrid clustering on the right.
Conclusion
A Hybrid Algorithm, is well-adapted to the clustering of large volumes of seismic data. The Hybrid Algorithm is based on the combination of two clustering techniques, hierarchical and K-means, referred to as Hybrid Clustering. The application of this innovative technology to multivariate seismic attributes in classifying seismic characteristics in the data has resulted in improved interpretive results (validated by well calibration and modelling). This technology was exhibited in two disparate case studies classifying AVO and elastic inversion attribute volumes, with the Hybrid Clustering technique enabling the validation and fine tuning of the original interpretation.

References