GC Benefits from Pattern Recognition and Visualization*

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Search and Discovery Article #41973 (2016)
Posted December 26, 2016

*Adapted from the Geophysical Corner column, prepared by the authors, in AAPG Explorer, December, 2016. Editor of Geophysical Corner is Satinder Chopra (schopra@arcis.com). Managing Editor of AAPG Explorer is Brian Ervin. AAPG © 2016

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General Statement

The need to effectively utilize the information in an ever increasing number of seismic data volumes can easily overwhelm the interpreter. However, recent developments in pattern recognition-based seismic facies classification (clustering) provide a means to analyze multiple seismic attributes in a single volume, either by color-coding seismic facies seen by the machine in an “unsupervised” fashion, or in an interpreter-driven, “supervised” fashion by extracting hidden relations between the attributes and a desired target property.

There has been extensive research in adapting pattern recognition techniques to seismic facies analysis, however the “soft” skill of visualizing and communicating the result to normal audiences is still more or less a privilege of the most experienced experts. In this article, we use a Barnett Shale survey to show not only how to perform an unsupervised classification with multiple seismic attributes, but more importantly, how to effectively visualize the result.

Geologic Features and Attribute Expressions

In the western portion of the Fort Worth Basin, the Barnett Shale lies directly on top of the dolomitic Ellenburger Goup. Karst and joints that extend upwards from the water-saturated Ellenburger into the Barnett Shale pose drilling and completion hazards. We use spectral decomposition, geometric and texture attributes to illuminate the architectural elements presented in the shallow part of the Ellenburger Group (Figure 1).

Karst collapses appear as a circular feature with positive (red) on the perimeter and negative (blue) in the center in both structural and amplitude curvatures, with amplitude curvature being more sensitive to subtle structures (blue arrows in Figure 1a and Figure 1b). Clusters of collapse and fractures are delineated in both structural and amplitude curvatures (yellow arrows). On the image of peak frequency modulated by peak magnitude (Figure 1c), we observe that karst collapses exhibit lower frequency compared to the surrounding area, possibly due to the non-specular scattering from the chaotic reflectors. On the same image, we use dip magnitude to represent the deformation along this surface. The dip magnitude highlights the highly karsted regions, as well as faults and folds. Note that most collapse features appear to be faultcontrolled (red arrows). Figure 1d co-renders gray-level co-occurrence matrix (GLCM) homogeneity with energy ratio similarity. Visually, areas that are less coherent are also less homogeneous, suggesting a more rugose surface.

These visual correlations of mathematically independent attributes for a given geologic feature provide an interactive, interpreter-driven means of selecting the most appropriate attributes for subsequent machine-driven classification.

Unsupervised Seismic Facies Classification and Visualization

To avoid mixing geology from other formations, we perform self-organizing map (SOM) analysis within a 50-millisecond time window below the top Ellenburger surface. While interaction with crossplots of three attributes (against x-, y- and color-axes) is simple, interacting with five attributes and a 5-D crossplot is intractable. SOM starts by fitting a 2-D plane to the 5-D crossplot. Projection of the 5-D data onto this plane provides a principal component map. SOM then deforms this plane into a curved 2-D surface to better fit the data. In order to use the display and interactivity of commercial software, we output these projected results as two volumes, one for each of the two axes of the 2-D surface. We assign two 1-D colorbars to each of the volumes, then crossplot the two volumes volumetrically. The two 1-D colorbars are designed to be two perpendicular axes of a color wheel (shown as the two dashed lines in the 2-D colorbar in Figure 2), so that when cross-plotted they form a 2-D colorbar of hue versus saturation.

At this point, the results are unsupervised. The interpreter assigns meaning by carefully analyzing representative facies of interest. On the SOM facies map, the karst-collapse regions appear in purple and cyan colors, where purple corresponds to anticlinal, and cyan to synclinal components of the features. Comparing to the co-rendered structural curvature, such karst features on the SOM facies map have a higher contrast to the surrounding regions, and have a cleaner silhouette, which benefits the interpretation of karst extent. Orange colors correspond to lower frequency, while yellow-green colors correspond to higher frequency non-karsted, non-fractured regions. We interpret the frequency change to be a measure of tuning thickness. In many cases, a best practice is to co-render an edge detection attribute (e.g. coherence) with SOM facies to highlight the boundaries of different facies. However, in this example the karst have multiple internal edges, which overprints our SOM classification (Figure 1d), therefore deteriorating the interpretability of the facies map.

To further calibrate different facies with seismic “ground truth,” we take four composite vertical sections (a) – (d), aiming to find seismic evidence of such facies. We co-render the self-organizing map (SOM) facies with seismic amplitude, and because we have to modulate the opacity of the SOM facies in order to allow the background seismic amplitude to come through, the colors on the vertical sections are faded compared to the map along horizon A. Horizon A lies vertically in the center of the SOM analysis window, so we expect to see the same facies from the horizon display shown at the center (vertically) of the colored zone on vertical sections. The karst-collapse features identified on horizon A nicely match the synclinal events on a seismic amplitude profile (marked as red curves), with the perimeter in purple (which fades to magenta on the vertical sections) delineating the extent.

We can also interpret faults from the seismic amplitude (blue curves), which are not well defined on the SOM facies because we did not include edge detection attributes as input. Most karst-collapse features developed along or in between two close faults, indicating that large-scale conjugate fractures might have accelerated the dissolution process of the Ellenburger Group.

Conclusions

In this article we show how to effectively use pattern recognition techniques with proper visualization to quantify the location and extent of subtle seismic facies in a 3-D volume. Unsupervised self-organizing map classification combines independent attributes to form a single color-coded facies map, which is then calibrated and validated with traditional seismic amplitude interpretation techniques. Crossplot tools provide a means of displaying each facies separately.

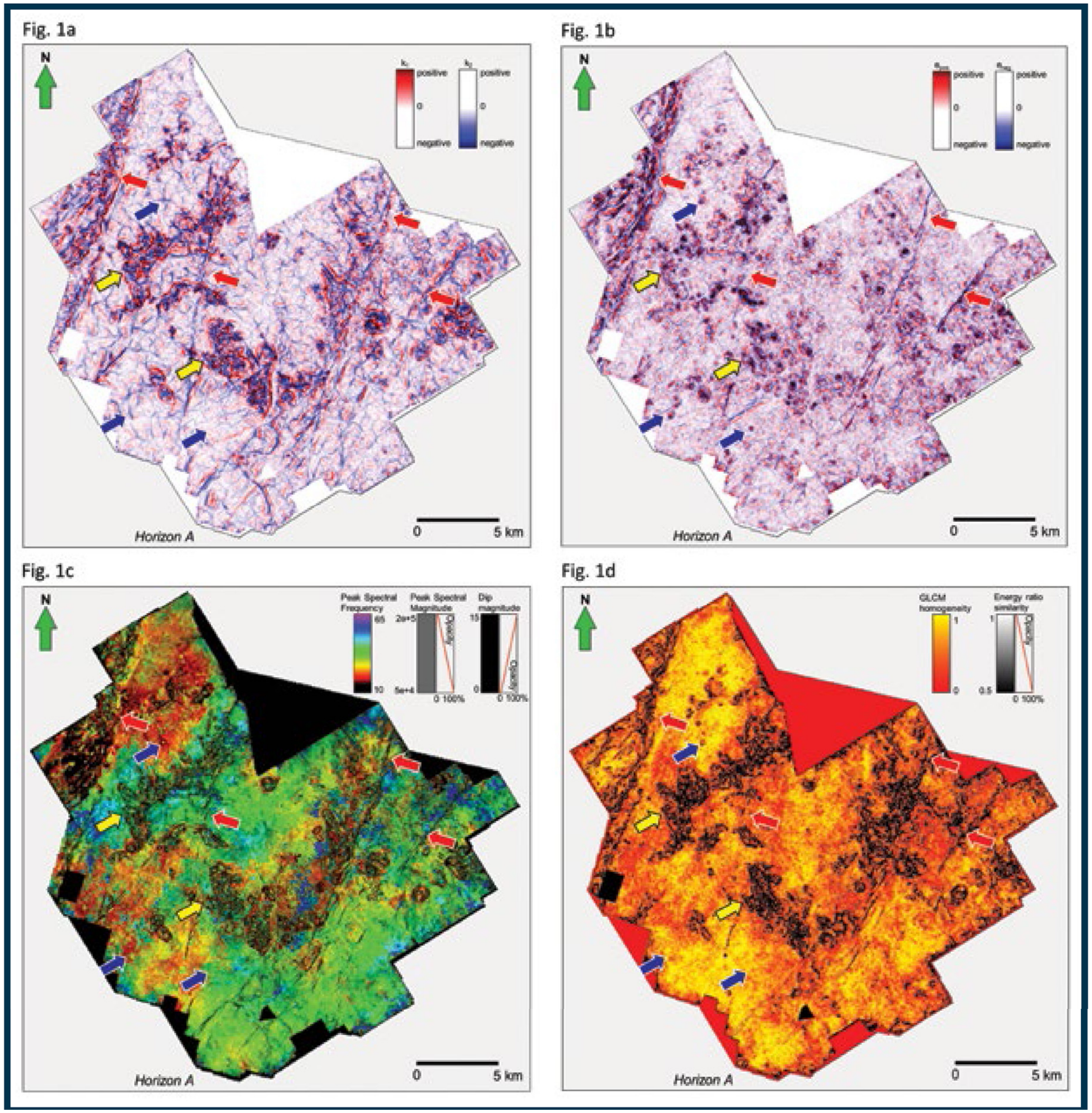

Figure 1. Attribute expressions of the Ellenburger Group along a phantom horizon A, 25 milliseconds below the top of Ellenburger. (a) Co-rendered most positive (k1) and most negative (k2) structural curvatures. (b) Co-rendered most positive (epos) and most negative (eneg) amplitude curvatures. (c) Co-rendered peak spectral magnitude, frequency at peak spectral magnitude and dip magnitude. (d) Co-rendered GLCM homogeneity and energy ratio similarity. In all figures, yellow arrows represent large scale karst-collapse clusters, blue arrows very small scale collapse and red arrows regional faults.

Fig. 2

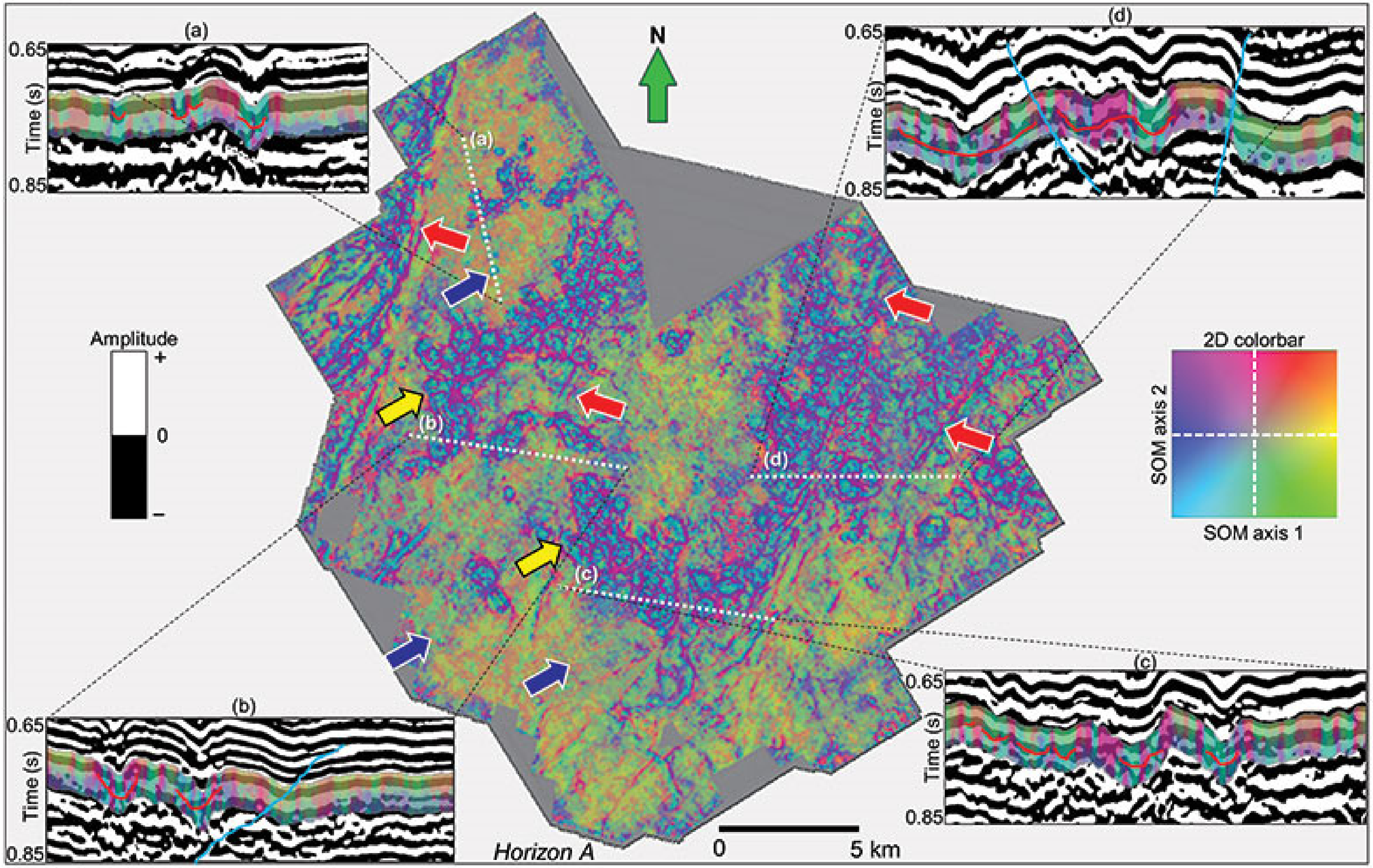

Figure 2. Self-organizing map (SOM) facies map displayed along horizon A using a 2-D colorbar. Inserts (a) – (d) are composite vertical sections at four different locations comparing SOM facies and seismic amplitude. All block arrows are the same as in Figure 1.