Integrated seismic texture segmentation and clustering analysis to improved delineation of reservoir geometry

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Summary

In recent years, 3D volumetric attributes have gained wide acceptance by geosciences interpreters. The early introduction of single-trace complex trace attributes was quickly followed by seismic sequence attribute mapping workflows. 3D geometric attributes such as coherence and curvature are also widely used. Most of these attributes correspond to a very simple easy-to-understand measures of a waveform or surface morphology. However, not all geologic features can be so easily quantified. For this reason, simple statistical measures of the seismic waveform such as RMS amplitude prove to be quite valuable in delineating more chaotic stratigraphy. In this paper, we show how modern texture analysis based on the gray-level co-occurrence matrix, when coupled with recent developments in self-organizing maps clustering technology, extends such statistical measures to delineate features that geoscientists can see, but not easily describe.

Introduction

One of the goals of the seismic interpreter is to analyze seismic amplitude and phase character in order to predict lithologic facies and rock properties such as porosity and thickness. Seismic attribute analysis is a technique that is commonly used by the oil industry to delineate stratigraphic and structural features of interest. Seismic attributes are particularly important in allowing the interpreter to enhance and visualize subtle features at or below the limits of seismic resolution. For example, coherence can generate easy-to-understand images of polygonally faulted shales that may be difficult to see on seismic amplitude time slices. Curvature can enhance long wavelength (500 -1000 m) flexures and folds in and out of the plane. Spectral components may highlight thin bed tuning effects buried in the seismic waveform.

Each of these attributes is based on a very simple geometric or physical model that can be related to structure, stratigraphy, diagenesis, or data quality. However, not all geologic features follow such a simple model. Experienced interpreters can easily recognize the seismic response of crystalline basement, mass transport complexes, and carbonate reef buildups. But when put to the task they find it difficult to quantitatively define how they do their interpretation. Such interpreters (and human beings in general) are experts at texture analysis. Our study focuses upon seismic texture analysis, borrowing upon techniques commonly used in remote sensing to map terrain, vegetation, and land-use information. Textures are frequently characterized as different patterns in the underlying data. Seismic texture analysis was first introduced by Love and Simaan (1984) to extract patterns of common seismic signal character. Recently, several workers (West et al., 2002; Gao, 2003; Chopra and Alexseev, 2005) have extended this technique to 3D seismic data through the use of the gray-level co-occurrence matrix (GLCM). GLCM allows the recognition of patterns significantly more complex than simple edges. GLCM-based texture attributes are able to delineate complicated geological features such as mass transport complexes and amalgamated channels that exhibit a distinct spatial pattern.

What is texture?

Texture is an everyday term relating to touch that includes such concepts as rough, silky, and bumpy. When a texture is rough to the touch, the surface exhibits sharp differences in elevation within the space of your fingertip. In contrast, silky textures exhibit very small differences in elevation. Seismic textures work in the same way, except elevation is replaced by brightness values (also called gray levels). Instead of probing a finger over the surface, a "window" or a square box defining the size of the area is used (Mryka, 2007).

The Grey Level Co-occurrence Matrix

GLCM is a tabulation of how often different combinations of voxel brightness values (gray levels) occur in a sub-image window. The Grey Level Co-occurrence Matrix introduced by Haralick et al.(1983) has been applied by Reed and Hussong (1989) Gao et al. (2002), and Gao (2003) to 3D seismic data in order to quantify seismic stratigraphic textures. Intuitively, we mentally apply texture analysis any time we view a shaded-relief time-structure map. We recognize piecewise-smooth surfaces separated by discrete faults, tightly folded areas, incised dendritic channels, and chaotic zones. Our method differs from others in that it is structural-oriented and can therefore be applied to structurally complex 3D seismic volumes. Given that the seismic wavelet modulates the reflection coefficients and hence the subsurface lithology, we feel that measures such as spectral decomposition do an excellent job of measuring amplitude variability normal to the locally dipping plane. Parallel to the local dip, we define a local analysis window. We also reformat the data from 32-bit data to 65 integer gray levels (with values 1-32 correlating to troughs, 33 to a zero-crossing, and 34-65 to peaks), constituting a "quantization" step. We compute the GLCM within a $(2m_x+1)$ by $(2m_y+1)$ window:

$$M_{ij} = \sum_{p=-m_x}^{+m_x}\sum_{q=-m_y}^{+m_y}\delta(d_{pq}-i)\delta(d_{p+\Delta p,q+\Delta q}-j) \tag{1}$$

where d_{pq} and d_{pq} are the integer-valued scaled seismic data at the (p,q) and $(p+\Delta p,q+\Delta q)$ CDP locations and the delta function, $\delta(\xi)=1$ if $\xi=0$ and 0 otherwise. We choose a suite of offsets Δp and Δq to represent repetative patterns at angles of $0^0,45^0,90^0,135^0$ to the acquisition axes. Since our input seismic (volumetric dip magnitude, or other attribute) data have been scaled to be integers between 1 and 65, our function M_{ij} can be written as a 65 by 65 matrix, **M**. Haralick et al. (1973) suggested 14 statistical measurements to describe a GLCM created from a moving window. Gao (2003) has added a few more. In this study, we use the four most-commonly used measurements of energy, *E*, contrast, C, homogeneity, H, and entropy, *S*.

$$C=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}M_{ij}(i-j)^2,\ H=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{M_{ij}}{1+(i-j)^2}$$

$$S=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}M_{ij}(\ln M_{ij}),\ E=\sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}M_{ij}^{\ 2}} \tag{2}$$

where N denotes the number of grey levels (in our case 65), and i and j are the rows and columns of the matrix **M**.

Summarizing, we need to define four items to use the GLCM

- the quantization level of the image,
- the size of the moving window,
- the direction and distance of voxel pairs, and
- the statistics used as a texture attribute.

Given these four parameters, texture images can be extracted using along local dip and azimuth and used as features for direct interpretation or subsequent multiattribute classification.

GLCM Worflow

Our 3D workflow is described by the flow chart shown in Figure 1. First, we precompute dip and azimuth at every seismic sample using one of several alternative 3D volumetric dip calculation algorithms. For reservoir studies, a sequence of stratal slices may be more appropriate. Next, we extract a $(2m_x+1)$ by $(2m_y+1)$ window of data for each and every output location. We then construct the GLCM using equation 1 followed by one or more attributes using equation 2. Finally we cluster these attributes using self-organizing maps for further interpretational analysis.

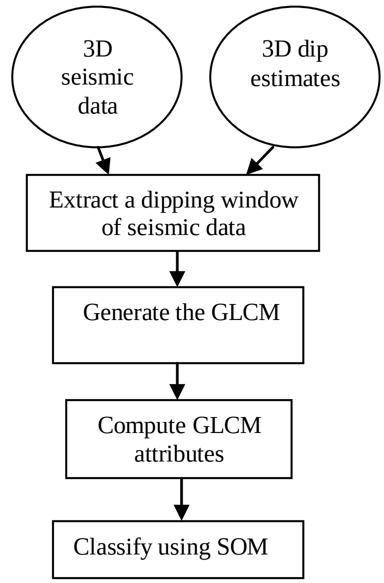


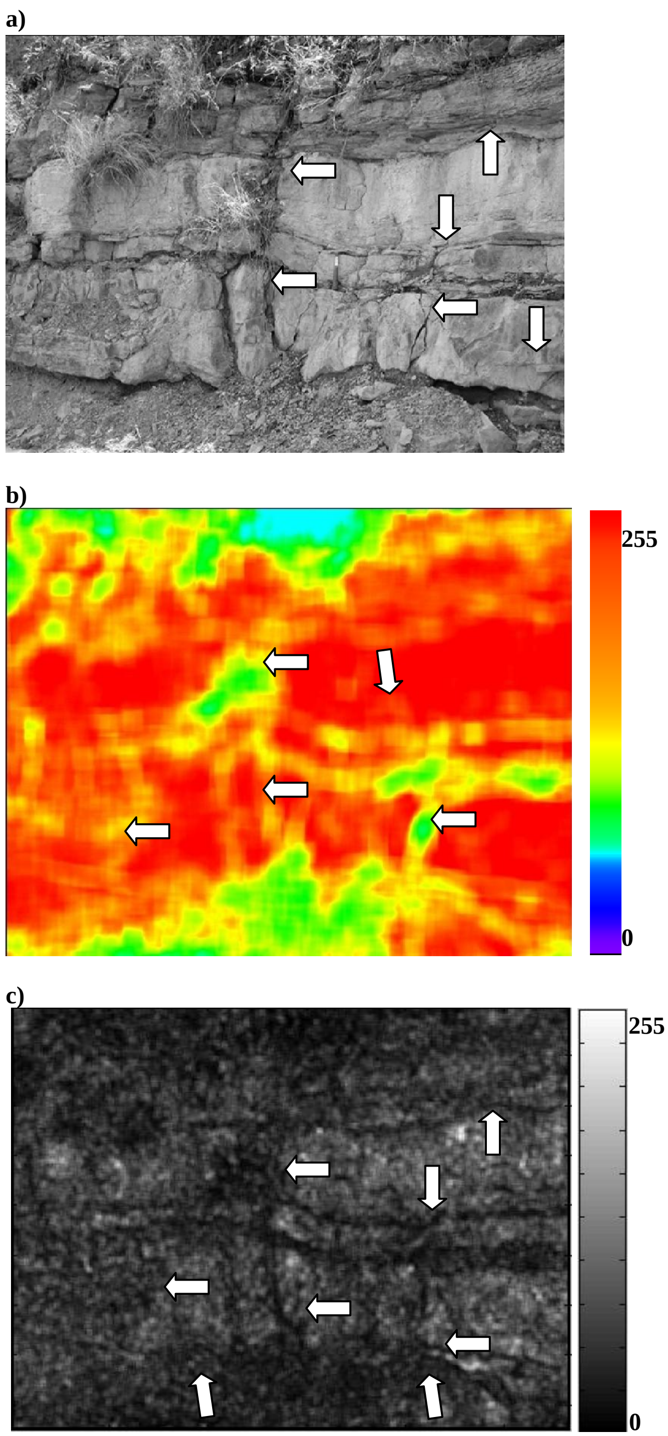
Figure 1. The 3D GLCM workflow.

Self Organizing map (SOM)

Self organizing maps, SOM, (Kohonen, 2001) and K-means clustering are the two most commonly used tools for non-supervised seismic facies analysis with SOM providing ordered clusters that can be mapped to a gradational color bar (Coléou et al, 2003). However, SOM can be interpreted as a mapping of the input *n*-dimensional input seismic attributes space onto a two-dimensional grid that preserves the original topological structure. Since seismic data measures the lateral changes in geology, SOM preserves the topological relation of the underlying geology (Matos et al., 2007). In this paper we assumed that the input variables to the SOM are the GLCM attributes and the resulting 2D SOM is colored against a 2D colorbar (Matos et al., 2009).

Application to a photographic of an outcrop image

To demonstrate how GLCM techniques are applied to remote sensing data, we apply it to a photographic image of the outcrop shown in Figure1 which shows fine-grained clay-rich limestones that occur in beds up to two feet thick with intervening shale layers. The photographic image size is 424 by 556 pixels, and is quantized into 256 grey levels. We used an 11 by 11 running window of ($m_x=m_y=5$) and computed matrices **M** and texture attributes at ($0^0,45^0,90^0,135^0$). After principal component analysis (PCA) of the collected texture images, PC components representing more than 99% of information were extracted for classification. Figures 2c and d, indicate that certain attributes shows distinct features compared to other attributes. After applying SOM, (Figure 2b) the fine-grained clay-rich limestones and the intervening shale layers were distinctly separated by the assigned quantization level.



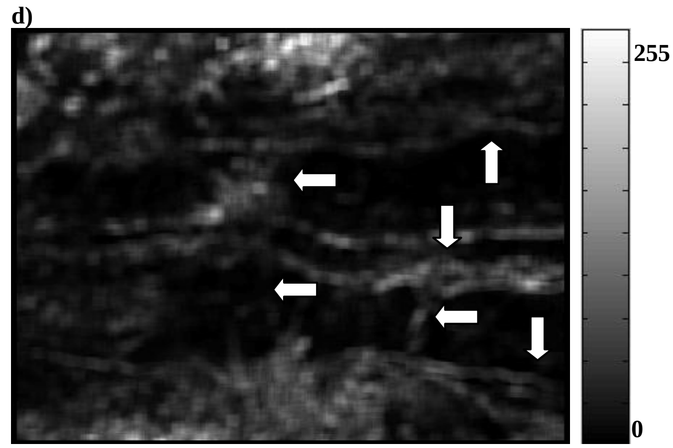
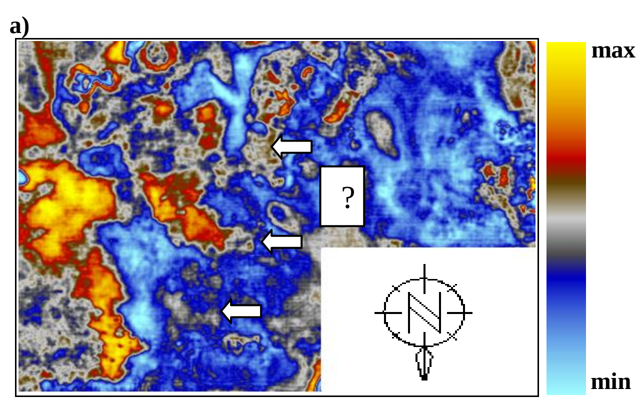


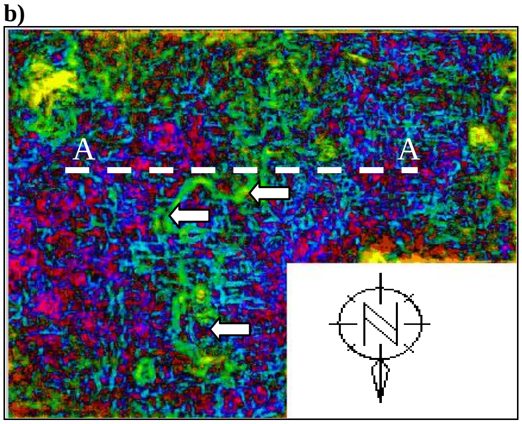
Figure 2. (a) Photo of an outcrop image of Monongahela Group, Pittsburgh Formation (from www.geology.pitt.edu). Block white arrows indicate texture characteristics espected to be seen after applying the GLCM and the SOM analysis. (b) Corresponding SOM 1D and GLCM (c) homogeneity 90^0, and (d) contrast attributes 90^0.

Application to 3D seismic data

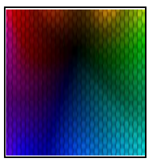
Given this visual calibration we turn our attention to a 3D seismic survey acquired in Osage County, OK, where our goal is to map subtle, thin-bed channels that form economic gas and oil reservoirs. The resulting texture and SOM analysis provides a clearer picture of the distribution, volume, and connectivity of the hydrocarbon- bearing facies in a reservoir facies know to have sand channels. Figure 3a shows to a horizon slice taken at 20ms below Oswego horizon through the seismic amplitude data. Figures 3b and c show the final 2D SOM and corresponding 2D color bar. Figures 3d and e show two representative, complementary, GLCM attributes - contrast and energy. These latter contrast and energy images have high amplitude values within the channel and intermediate values in what we interpret to be the channel levee.



b)



c)



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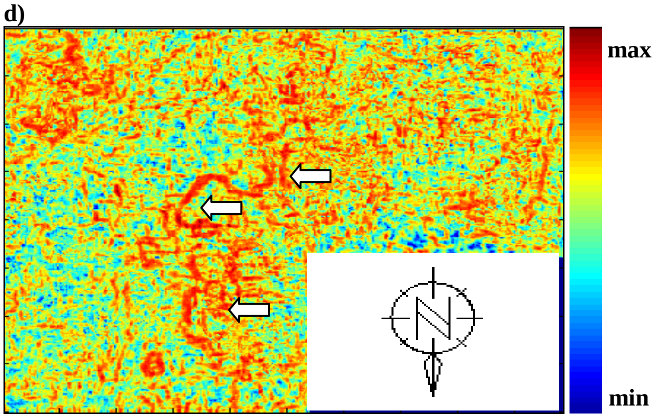

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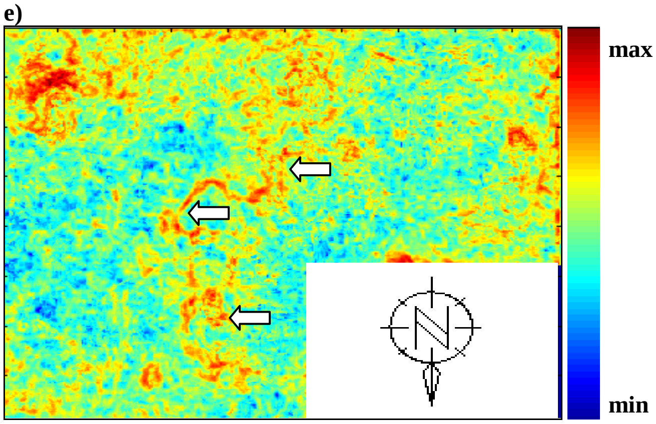

f)

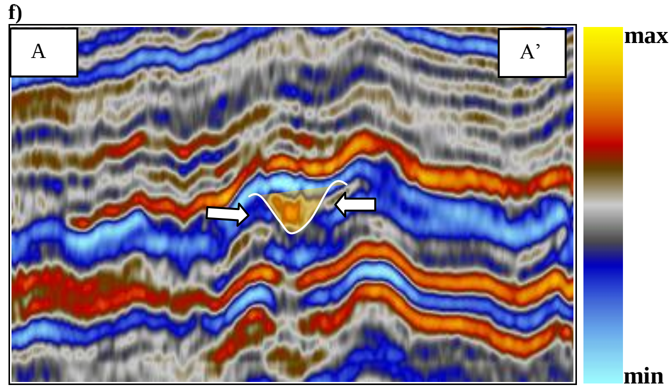

Figure 3. (a) Horizon slice 20ms below the Oswego horizon showing a suspected channel. Block white arrow indicates a channel-levee complex. (b) SOM clusters computed using GLCM contrast, and energy attributes compute at 0, 45, 90, and 135 degrees with offests Δp, $\Delta q = 0$ or 1, (d) 2D SOM 256-class topology mapped against a 2D 256-colorbar. Horizon slices through representative GLCM (d) contrast and (e) energy attribute volumes indicating the channel levee complex. (f)Vertical slice AA' through the seismic amplitude volume showing the channel.

Conclusion

2D seismic stratigraphy is based on human interpreter identification of subtle textures, such as onlap, offlap, unconformities, hummocky clinoforms, and parallelism. With the aid of attributes, 3D seismic geomorphology extends these concepts to volumetric data. GLCM technology is a preliminary attempt at quantifying these relationships for further analysis using computer vision. Texture attributes hold significant promise in quantifying geological features such as mass complex transport, amalgamated channels, and dewatering features that exhibit a distinct lateral pattern beyond simple edges.

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