IMAGE PROCESSING OF ACOUSTIC MICROSCOPY DATA TO ESTIMATE TEXTURAL SCALES AND ANISOTROPY IN SHALES

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Abstract: We estimate different statistical measures for quantifying heterogeneity and textures from scanning acoustic microscope images of shale microstructures. The analyzed shales covered a range of depths, kerogen content, and maturity. We observed quantifiable and consistent patterns linking texture, shale maturity, and elastic P-wave impedance. The textural heterogeneity and P-wave impedance and velocity, and density increase with increasing maturity (decreasing kerogen content), while there is a general decrease in textural anisotropy with maturity. We also found a reasonably good match between elastic impedance estimated from SAM images and impedance computed from ultrasonic measurements. The textural anisotropy ranges from 10% to about 70% and tends to decrease with increasing depth and maturity.

Key words: Kerogen shales, acoustic microscopy, Image processing, Fourier transform

1. INTRODUCTION

Microgeometry plays an important role in the overall effective elastic properties of shales. Therefore characterizing and understanding the microgeometry, their textures, scales, and textural anisotropy is important for better understanding the effect of microgeometry on effective elastic properties. Microstructural characteristics of organic rich shales can give important insights on the maturation processes and on oil generation from such formations (Vernik and Nur, 1994). Optical and scanning electron

microscopy methods to analyze kerogen shale microstructure have been utilized in the past. However, due to the opaque nature of the kerogen and the associated pyrite, such methods are rather difficult to implement. For example, studies have shown that microgeometry, textural heterogeneity, and textural anisotropy have significant effects on the effective elastic properties of rocks. On the other hand, Prasad et al. (2002) have shown we can map textural changes with shale maturity with acoustic microscopy.

2. METHODS

The acoustic images were made with an acoustic microscope and image analyses techniques are used to detect changes in texture and heterogeneity in these images.

2.1 Acoustic Microscopy

We used a non-destructive technique to map the impedance microstructure of kerogen-rich shales with a Scanning Acoustic Microscope. The C-scan surface images were made at 1 GHz. With this technique we were able to map changes in elastic properties as the shales undergo maturation. The method and sample description and impedance measurement on a micrometer-scale is given in detail in Prasad et al. (2002).

2.2 Image Processing

The heterogeneity was quantified by the coefficient of variation (CV, standard deviation/ mean) of the image pixel values. Textures were quantified using spatial autocorrelation functions. We used Fourier transform based autocorrelation estimation. Radial profiles of the autocorrelation function along azimuths ranging from 0° to 180° were computed, and the correlation length estimated at each azimuth. The texture anisotropy was quantified by the anisotropy ratio (AR) defined as the ratio between the maximum and minimum correlation lengths obtained over all azimuths.

We used statistical descriptors to quantify the heterogeneity and textures observed in the images. The heterogeneity was quantified by the coefficient of variation (CV) given by the ratio of the standard deviation to the mean of the image pixel values. Spatial textures can be quantified using spatial autocorrelation functions R(m,n). As an example, Fig. 1 shows how a smoothly varying image has a broad, slowly decaying autocorrelation function. In contrast a rough “salt-and-pepper” image has a very narrow spiky autocorrelation function.

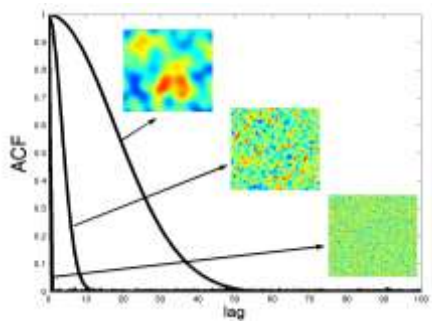

Figure 1. Relation between the autocorrelation function and synthetic images.

We used Fourier transform based autocorrelation estimation where

$$R(m,n) = F^{-1}\left[S(kx,ky)\right]$$

$$S(kx,ky) = \hat{I}(kx,ky)\hat{I}^{*}(kx,ky)$$

$$\hat{I}(kx,ky) = F[I(x,y)]$$

In the above equations I(x,y) denotes the image intensity, while F and F^{-1} denote the forward and inverse Fourier transforms. The 2-d Fourier transform of the image I(x,y) is denoted by $\hat{I}(kx,ky)$ where kx, ky are the spatial wavenumbers in the Fourier domain. The power spectrum S(kx,ky) is obtained by multiplying $\hat{I}(kx,ky)$ with its complex conjugate. Finally the 2-d ACF R(m,n) is obtained by taking the inverse Fourier transform of S.

In Fig. 2, the synthetic textures image is shown on the left and its corresponding 2-d autocorrelation function (ACF) is on the right. Peak intensity is the autocorrelation at zero lag distance (maximum) and decays away on all sides with increasing lag. The rate of decay is a quantitative measure of texture. Radial profiles of the autocorrelation function along azimuths ranging from 0 to 180 degrees were computed by interpolation along the different directions, and the correlation length estimated at each azimuth. This analysis, shown in Fig. 3, allowed us to quantify the azimuthal changes in ACF due to textural anisotropy. As Fig. 3 shows, the correlation length at each azimuth is taken to be the lag value where the correlation function falls to 1/e of its maximum value at zero lag. The texture anisotropy was quantified by the anisotropy ratio (AR) defined as the ratio between the maximum and minimum correlation lengths obtained over all azimuths. All 180 ACF profiles are plotted in Fig. 3. Figure 4 and 5 show examples of actual shale SAM images and corresponding radial profiles of the ACF.

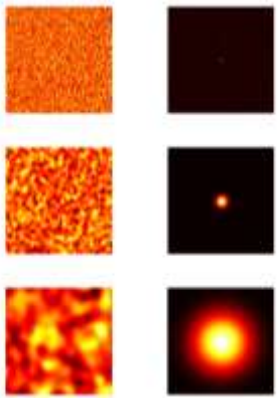

Figure 2. Synthetic textures and their two-dimensional ACF

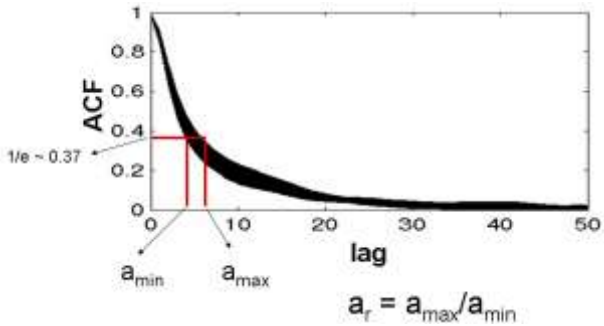

Figure 3. Radial profiles of the 2D autocorrelation along all azimuths from 0° to 180°.

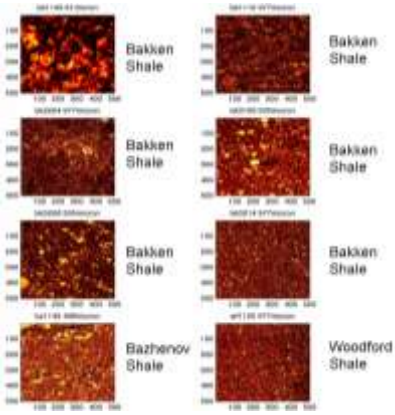

Figure 4. C-scan images made at 1 GHz with the Scanning Acoustic Microscope (SAM).

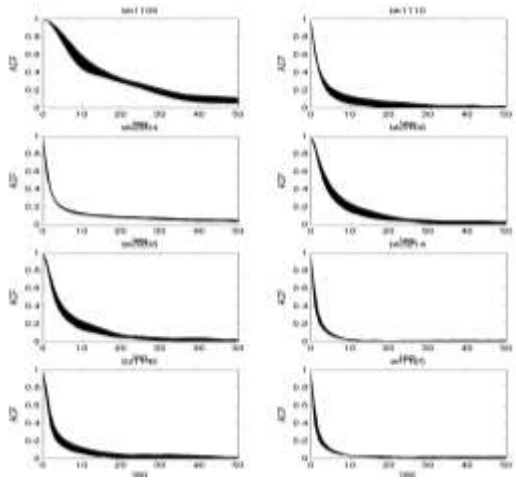

Figure 5. Radial profiles of the ACF from 0 to 180 for the SAM images in Figure 8.

Thus, we define three parameters for textural analysis:

- The Coefficient of Variation (CV) that describes textural heterogeneity. A larger contrast of heterogeneity leads to high values of CV
- The Anisotropy Ratio (AR) that describes the textural anisotropy. Textural anisotropy leads to a directional dependence of the ACF.
- The Mean Correlation Length that describes textural scale in the images. Larger sized heterogeneities lead to longer correlation lengths

In the following, we present analysis of all the shales.

3. RESULTS

This paper shows how can we quantify textural changes and relate them to maturation and ultrasonic properties of Vp, density, and impedance. Of the dataset used in Prasad et al. (2002), we have analyzed 3 shales: Bakken, Bazhenov, and Woodford. These are organic rich shales with varying amounts of kerogen content, at different maturation stages, and from different depths. We analyzed over 280 SAM images takes at different scales ranging between ~0.1 – 1mm image size and ~0.2 – ~2µm pixel resolution.

3.1 Image Processing Results

The results of texture analyses are discussed below and shown in the following figures. The data points plotted in the figures are averages over multiple samples, with one standard deviation bars around the estimated

average. The coefficient of variation (CV) of the impedance heterogeneities ranged from about 7% to 12%. The mean correlation length ranged from 2 to 10 microns while the textural anisotropy ratio ranged from 1.1 to 1.7 (10% to 70%). We will examine the patterns between textural anisotropy and mean correlation length (Fig. 6), and between textural heterogeneity and correlation length (Fig. 7). We will also see how these patterns change with depth and maturity.

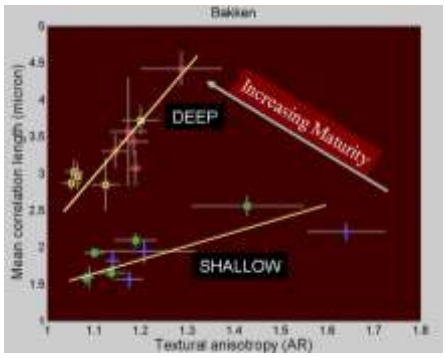

Figure 6. Mean correlation length as a function of textural anisotropy (AR). Woodford shale are shown as circles; Bazhenov shale as triangles; and Bakken shale as squares.

In general, textural anisotropy (AR) increases with increasing mean correlation length (Fig. 6). With depth (= maturity), textural anisotropy increase is lower while the mean correlation length increase is larger. Deeper samples have lower anisotropy but larger heterogeneities. This trend can be sub-divided further within each set. For example, in Bakken shales, the AR vs. mean correlation length trend steepens with depth; that is, textural anisotropy decreases while mean correlation length increases as we go from shallow (less mature) to deeper (more mature) shales.

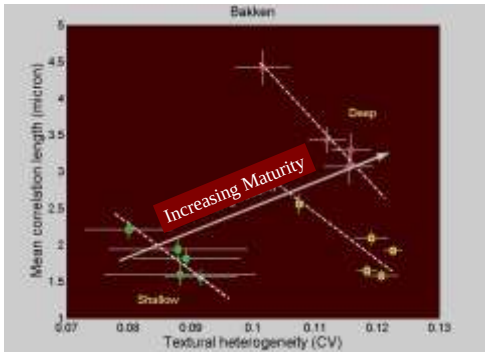

Figure 7. Mean correlation length as a function of textural heterogeneity (AR).

The textural heterogeneity and mean correlation length show a en-echelon correlation pattern when we plot the Bakken samples seperated by depths (Fig. 7). For each depth we see a negative trend between heterogeneity and correlation length, but overall there is a trend of increasing heterogeneity and correlation length with increasing depth and maturity. This is consistent with the observed trend of increasing heterogeneity (CV) with decreasing kerogen content and total organic content (TOC) (Fig. 8).

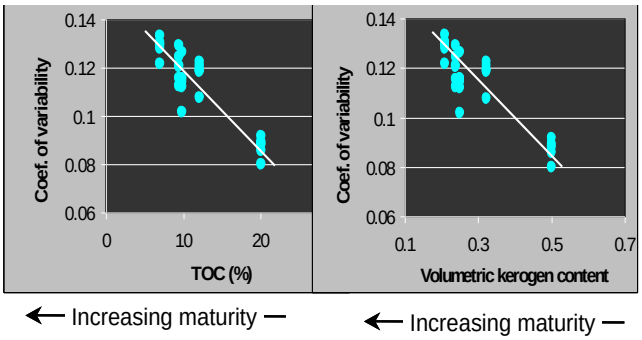

Figure 8. Coefficient of variability (textural heterogeneity) increases with decreasing kerogen content and total organic content.

3.2 Correlations with other measurements

A satisfying match was obtained between P-wave impedance derived from the SAM images and the corresponding impedance from ultrasonic data on core samples (Fig. 9). Fig. 9 shows the ultrasonic impedance derived from measured V_P along both the fast and the slow directions (small dots), along with the SAM impedance (large red and orange dots) for Bakken shales. Elastic impedance, density and textural heterogeneity all increase with increasing maturity (Fig. 9).

4. DISCUSSION / CONCLUSIONS

Our analysis of textural parameters of SAM images from Bakken, Bazhenov, and Woodford shales showed quantifiable and consistent patterns linking texture, shale maturity process, and elastic P-wave impedance. Image derived impedances matched reasonably well with impedances estimated from ultrasonic data. The coefficient of variation, CV, (textural heterogeneity) ranges from 7% to about 12% for these samples. Textural

heterogeneity, elastic impedance, P-wave velocity, and density all tend to increase with increasing shale maturity. The mean spatial correlation length generally tends to increase with increasing heterogeneity. The textural anisotropy (AR) ranges from 10% to about 70% and tends to decrease with increasing depth and maturity.

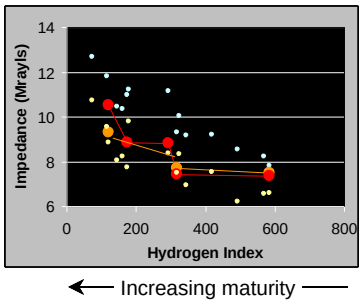

Figure 9. Consistency between P-wave impedance from SAM images (large red and orange spots) and impedance estimated from ultrasonic data (small dots). Ultrasonic data is from Vernik and Nur, 1994). Impedance shows a general increase with increasing shale maturity (from Prasad et al., 2002).

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