Azimuthally Sectored Attribute Volume Analysis

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Fracture detection and characterization is a critical aspect to successful shale plays. This is the case whether the play is enhanced or inhibited by the existence of natural or hydraulically induced fractures. In the Barnett Shale, Fort Worth Basin, areas of fractures should typically be avoided. Through the use of full azimuth 3D seismic data with attributes highlighting the differences in frequency, time and amplitude we can effectively isolate areas of fractures (Tod et al 2007). This paper will discuss how these attributes can be high-graded based on azimuthal variations.

In April 2009, Devon Energy acquired a wide azimuth 51 km^2 proprietary 3D seismic survey over the study area. During processing, the azimuthal velocity variation based on the far-offset azimuthal variation in travel times was computed. The data was then prestack time-migrated, and four 45^0-wide azimuthally-sectored volumes centered about 0^0 (North), 45^0, 90^0, and 135^0 were generated for further analysis. To improve fold and signal to noise ratio, the four azimuthal sectored volumes were binned at 220 ft by 220 ft (67 m by 67 m). This processing has also been implemented in other 3D surveys in the study area.

Within this survey there are several hundred Devon-operated Barnett gas wells, two thirds of which are vertical or directional and the remainder are horizontal wells. The wells are believed to be producing from open, hydraulically-induced fractures, and if orthorhombic symmetry is present (flat layers and one dominant set of vertically-aligned open fractures), then we hypothesize that we should be able to detect open fractures with seismic (Lynn 2004). We expect the effective intensity of fractures detected to vary by azimuth. Knowledge of fast and slow azimuth directions, velocity anisotropy trends and behavior of the microseismic data will aid in confirming this expectation.

Typically seismic attributes are run on full-azimuth, full-offset stacked data. In our study a full suite of 180 attributes were run by a third party vendor on each of the four azimuthally-sectored PSTM volumes. A total of six horizons above and below the zone of interest were picked on each azimuthally-sectored volume to avoid the overprint of the time-delay anisotropy.

We chose three horizons above the zone of interest, one at the top of the Barnett Shale, one within the Barnett Shale and one below. Two of the six horizons were not picked on a reflector, but were a reflector pick plus 20 ms to validate the azimuthal variations that were being seen on a horizon and ensure that we were not missing any attributes that may be varying within the zone of interest. Multiple horizons are necessary because we are interested in attributes that show azimuthal variability in one horizon and not another because we believe the Barnett Shale is more highly fractured due to hydraulically-induced fractures.

These attribute values are then fit to an ellipse using the same principals Gretchka and Tsvankin (1998) used to approximate the NMO velocity in a medium with horizontal transverse symmetry. Following the methodology of Thompson et al (2010) ellipses were fit for each attribute. For our purposes we will only need to inspect the eccentricity of the best-fit ellipse given by

$$e = \sqrt{1 - \left(\frac{\lambda_2}{\lambda_1}\right)^2}\,, \qquad (1)$$

where λ_1 and λ_2 are major and minor axes of the ellipse, while the reliability of the fit is defined as

$$R = \frac{e}{RMSE}. \qquad (2)$$

where RMSE is the Root mean square error for the best fit ellipse.

After the ellipse fitting on the individual horizons, we ranked the attributes by the highest reliability, R, as seen in equation 2, for each horizon. We also ran the best-fit ellipse on a set of random data to ensure the reliabilities we were seeing for our horizons were valid. The median reliability for a random data set was approximately 5. Median reliabilities calculated on the horizons ranged from about 4 to 7. Attributes with reliability near 4 were inappropriate for ellipse fitting because they were binary attributes and were disregarded. A list of the top 10 attributes with the highest reliabilities was made for each of the 6 horizons. From the individual lists we selected 25 attributes for a more in-depth review. The 25 selected attributes consisted of several attributes that appeared in the list of multiple horizons' top reliabilities and some attributes that only appeared in one horizons' top reliability list.

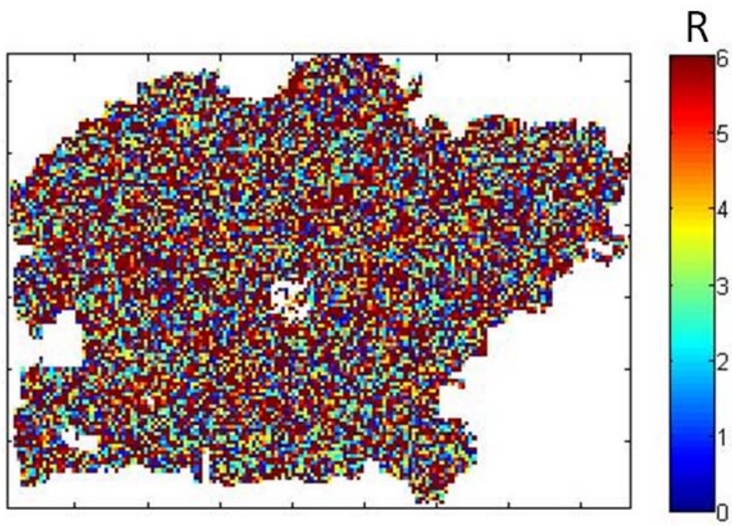

Figure 1. The reliabilities for a random

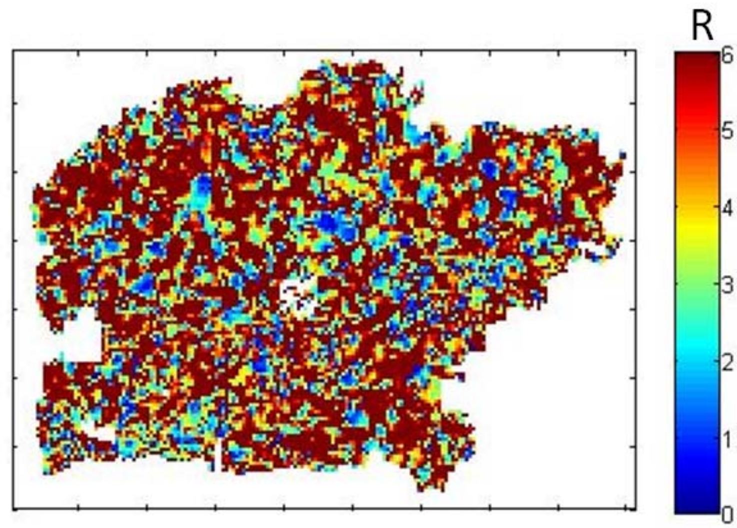

Figure 2. The reliabilities for the Gabor-Morlet Decomposition envelope sub band.

Among the highest ranked attributes were several of the Spectral Decomposition computations. These attributes use the Gabor-Morlet Decomposition and then have the envelope amplitude, phase and trace values computed over a linear range from 10 Hz to 90 Hz in 5 Hz increments. The envelope and phase of the sub bands in the lower frequency Spectral Decomposition attributes show the most azimuthal variation. Other attributes accentuating frequency and amplitude differences also show high azimuthal variability. We would expect a larger effect in the lower frequencies as well as differences in frequency and amplitude due to the effect of hydraulically-induced fractures.

Next, the eccentricity, e, as seen in equation 1 was mapped and compared for the top 25 attributes for each horizon. Eccentricity maps were compared between all horizons. Degrees of eccentricity are expected to be varying the most between the top and base of the Barnett Shale where there are induced fractures. Attributes with no change in eccentricity within the Barnett Shale interval were then thrown out leaving a manageable sample of attributes to use in further studies.

Through the use of fitting an ellipse to our azimuthally sectored attribute data we were able to quickly and successfully identify the most significant attributes from a set of 180 attributes. We were then able to high-grade the attributes in order to effectively map hydraulically-induced fracture zones. Additional work will quantify the correlation between production data and the high-graded seismic attributes.