SEISMIC ATTRIBUTES ILLUMINATION OF THE WOODFORD SHALE,
ARKOMA BASIN, OKLAHOMA

A THESIS
SUBMITTED TO THE GRADUATE FACULTY
in partial fulfillment of the requirements for the
Degree of
MASTER OF SCIENCE

By

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Norman, Oklahoma
2010
SEISMIC ATTRIBUTES ILLUMINATION OF THE WOODFORD SHALE,
ARKOMA BASIN, OKLAHOMA

A THESIS APPROVED FOR THE
CONOCOPHILLIPS SCHOOL OF GEOLOGY AND GEOPHYSICS

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In memory of my initial advisor, Dr. Roger A. Young
ACKNOWLEDGMENTS

I would like to give my sincere thanks to my kind advisor Dr. Kurt J. Marfurt for providing me the opportunity to study at the University of Oklahoma. My Master’s program would not be finished without his great support and guidance. I will never forget his encouragement and understanding in my life aspect. Thanks to my committee, Dr. Roger M. Slatt and Dr. J. Timothy Kwiatkowski, for their commitment to be my Master’s committee and their helpful guidance. Special thanks to Jeremy Fisk, my old colleague, for his great help in the data acquirement and in the Petrel project. Thanks to the school staff: Donna, Nancy, Teresa, Niki and Adrianne.

To my family, my husband Kui Zhang has given me so much love and support in my life. My parents have provided the critical help after my daughter Ana was born. This work is dedicated to them with all of my love.

I thank Pablo LLC, BP, and CGG-Veritas for providing the data and the authorization to publish this work. Thanks to OU Petroleum Engineering colleagues for making the core analysis. Thanks to Schlumberger and Hampson-Russell for providing software licenses for use in research. Initial support was provided by seed funds from Benham group of SAIC.
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The Woodford Shale formation of south-western Oklahoma is hydrocarbon-rich shale that has served as the source rock for many Oklahoma oil and gas plays over the past century. Today, the Woodford Shale is an unconventional resource play similar in age and depositional environment to the prolific Barnett Shale. Like the Barnett, the Woodford Shale contains a large amount of healed natural fractures, has very low permeability, and is amenable to production through hydraulic fracturing. Unlike the Barnett, the Woodford Shale can also produce significant amounts of oil as well as gas. The characterization of fracture intensity and orientation has a direct impact on horizontal well orientation and completion strategies.

Volumetric seismic attributes allow interpreters to map the structural deformation and subtle stratigraphic details that are not readily observable on seismic data. In the study, I used the multi-trace geometric attributes and impedance volumes to investigate the fracture patterns in the Woodford Shale. Coherence allows us to map relatively large offset discrete faults that appear to have a wrench component, while structural curvature allows us to map subtle folds and flexures. Low acoustic impedance anomalies have a strong correlation with structural lineaments given by curvature and coherence, strongly suggesting either natural fractures or diagenetic alteration. Analysis of the production data indicates that the best-producing wells correlate to zones associated with $k_2$ most negative principal curvature (valley-shaped) anomalies and fractures from 30° and 60° to the North. The proximity of microseismic events to ridge/dome features suggests that, the ridge/dome features may consistent with the paleo-zones of structural weakness.
CHAPTER 1 INTRODUCTION

Given an abundance of well control, mature shale gas plays do not require 3D seismic data to estimate the depth and thickness of the reservoir. Rather, the application of 3D P-wave seismic data in shale gas reservoirs has focused on predicting geo-mechanical brittleness and horizontal stress directions for effective hydraulic fracture stimulation. 3D P-wave seismic can also help map natural fractures and collapse features that can provide enhanced conduits for hydrocarbons, or in the case of the Fort Worth Basin, water from the underlying Ellenberger carbonate formation. For effective fracability studies, core data and lab measurements of rock samples and logs are critical, providing calibration of elastic parameters extracted from seismic data to identify fracture-prone zones. For example, Goodway et al. (2006; 2007a) suggest using $\lambda \rho$ (incompressibility) and $\mu \rho$ (rigidity) to predict geo-mechanical brittleness in the Barnett Shale. 3D Amplitude vs. Azimuth (AVAz) (Ruger, 1998; Goodway et al., 2007b), and Velocity vs. Azimuth (VVAz) (Jenner, 2001; Sicking et al., 2007; Roende et al., 2008) reveal the anisotropy due to fracture or stress, providing a direct measure of fracture azimuth and intensity. P-wave AVAz and VVAz require 3D wide azimuth seismic data with adequate fold and work well when there is a single dominant fracture set (giving rise to Horizontal Transverse Isotropy). Jianming et al. (2009) find that delay times and polarization of shear waves work well for multiple fracture sets.

Structural curvature computed from migrated 3D seismic data volumes provides measures of faults, flexures, and folds (e.g. Chopra and Marfurt, 2007). Although curvature measures do not directly detect open fractures, case studies (Murray, 1968;
Lisle, 1994; Hart et al., 2002; Blumentritt et al., 2006; Nissen et al. 2009) have shown the success of using curvature maps to predict fractures. Lisle (1994) made one of the earliest detect/calibration of curvature to fractures using outcrop measurements and found a strong correlation between Gaussian curvature (described by Chopra and Marfurt, 2007) and open fractures. Hart (2002) found a close correlation between the strike component curvature and fractures based on a producing field in north-western New Mexico, U.S.A. Nissen (2009) recognized that the well’s distance to the closet interpreted most negative curvature lineament has a close correlation with production. Well control showed these lineaments to be expressions of diagenetically altered fractures.

In general, flexures or folds in brittle rocks will generate fractures which may not readily be seen on any post stack seismic attributes. Rather, detailed structural deformations revealed by curvature images need to be coupled to local stress orientation from either pre stack AVAz or VVAz, or fracture directly seen on image logs, through an appropriate tectonic deformation model, in order to identify potential fracture swarm sweet spots. Hunt et al. (2010) found that AVAz, VVAz, and curvature attributes are strongly correlated to image log fracture density and to the location of microseismic events induced by hydraulic fracturing. Simon (2004) found good visual correlation between azimuthal interval velocity anisotropy, induced fracture patterns mapped by microseismic measurements and expected ultimate recovery (EUR). Xavier (2009) found microseismic events within the Barnett Shale do preferentially favor low S-impedance zones.

In the main part of this thesis, I investigate a study of fracture illumination in the Woodford Shale of the Arkoma Basin through seismic attributes analysis. I begin with a
geologic overview of the Woodford Shale. Next, I image natural faults, flexures and potential fractures using coherence, volumetric curvature and acoustic impedance. Other attributes such as rose diagrams and RMS amplitude are also employed to assist the fracture study. Then I correlate natural fracture lineaments seen on structural curvatures with production data. Azimuthal intensity was employed to quantitatively correlate with production in an attempt to predict fluid flow in Woodford Shale. Finally, I demonstrate that, induced fractures mapped by microseismic data preferentially occur in zones of low impedance and ridge/dome features. In addition to interpreting the Woodford Shale using seismic attributes, I perform the seismic inversion analysis of the Woodford Shale as a complementarity of my thesis study, which I put in the Appendix.
CHAPTER 2 GEOLOGICAL BACKGROUND AND DATA AVAILABILITY

2.1 Geological background

Due to the recent advancements in hydraulic fracturing technology to create reservoir permeability, the Mississippian and Devonian Woodford Shale gas has become an increasingly important resource play in U.S.A. The area under study is located in Arkoma basin in southern Oklahoma.

![Map of Oklahoma showing geologic provinces](image)

Figure 2.1 Major geologic provinces of Oklahoma. The Arkoma Basin is colored blue and lies in SE OK. (After Northcutt and Campbell, 1995).

The late Devonian to early Mississippian Woodford Shale is deposited from 6000 to 12000 ft in depth over the Hunton group marked by an unconformity (Figure 2.2). The thickness of the Woodford Shale ranges from 120 to 280 ft. The Woodford Shale formation is an organic-rich, fissile black shale which is probably deposited in a deep marine environment, under highly anoxic conditions. According to the study shown by Cardott (2007), the Woodford Shale can be divided into three members: the Lower Woodford Shale, Middle Woodford Shale, and Upper Woodford Shale. The Lower
Woodford Shale was deposited close to the shore environment, and composed of quartz silt and clay. The Middle Woodford Shale was deposited farther from the shore facies during a sea level rise which has a very high total organic content (TOC) showing high Gamma Ray value. The Upper Woodford Shale has very low TOC content deposited during a period of marine regression.

![Stratigraphic column of Arkoma Basin](image)

Figure 2.2 Stratigraphic column of Arkoma Basin (Portas, 2009).
Figure 2.3 Comparison of composition between Woodford and Barnett Shale. Others=Orthoclase Feldspar, Oligoclase Feldspar, Albite, Anhydrite, Pyrite, Apatite. Much of the quartz in the Woodford formation is Chert. (Core measurements courtesy of OU rock physics lab).

Figure 2.4 Rock samples of Woodford shale that serve as (a) tight source and (b) fractured reservoir rock (Photos of display samples in the Oklahoma Geological Survey).

Compared to the Barnett Shale, the Woodford Shale also contains high organic content (making it a prime petroleum source rock in Oklahoma) (Figure 2.4a), as well as a major quartz component (primarily chert) which allows the rock mass to be readily fractured (Figure 2.4b). Open fractures in shale provide critical porosity and permeability,
while healed fractures can be opened for hydrocarbon flow through carefully-designed hydraulic fracturing programs. Like the Barnett, the Woodford Shale contains a large amount of healed natural fractures, has very low permeability, and is amenable to production through hydraulic fracturing.

Figure 2.5 Main faults system surrounding survey area. (Modified from Northcutt and Campbell, 1995)

The Woodford Shale has been subjected to several episodes of tectonic deformation, resulting in multiple fault systems in the reservoir as shown in figure 2.5. A major period of folding, faulting, and uplifting in southern Oklahoma began during the Pennsylvanian period, giving rise to the Wichita orogeny in southwest Oklahoma. During the Middle Pennsylvanian, the Ouachita orogeny caused strong deformation of the sediments in the Ouachita Basin and formed the Ouachita Mountains. The erosion of rocks of the Ouachita Mountains produced a large volume of sediment that was deposited to the north in the newly formed Arkoma Basin. By the Late Pennsylvanian, the Arbuckle orogeny occurred, and reactivated mountain building and uplift of all regions in southern Oklahoma.
2.2 Data availability

There were four data sets available for my thesis study (shown in Figure 2.6a). The seismic data includes a 160 square miles post-stacked data volume and a 4 square miles time migrated pre-stack data. Besides the seismic data, there were 22 wells with production data in the big survey, and 2 wells with microseismic data used to calibrate and correlate the fracture framework with seismic attributes. One well within the area of small pre-stack dataset has P-wave, S-wave, density logs which was used to do inversion analysis. The core interpretation result from this well provides the opportunity to compare the mineral composition of Woodford Shale with Barnett Shale. Figure 2.6b gives the distribution of all the available data under the study.

Figure 2.6 Data available for the thesis study. (a) Four types of data sets in this thesis project. (b) The time structure map showing the distribution of all the data. The small blue rectangle indicates the location of the small pre-stack data under the study. Vertical lines indicate the wells with production data in this survey.
CHAPTER 3 SEISMIC GEOMETRIC ATTRIBUTES ANALYSIS

In recent years, seismic attributes have proven to be a powerful aid in mapping subsurface geological features. With sufficient well control, seismic attributes can detect subtle but important structural or stratigraphic components that can be statistically correlated with production (e.g. Nissen et al., 2008).

3.1 Imaging natural faults and fractures

Figure 3.1 shows a time structure map of the Woodford horizon. In addition to a major wrench fault cutting the horizon into a shallower northern and deeper southern section, we note a fault indicated by the block yellow arrow in the image.
Figure 3.2 shows a conventional RMS amplitude image, calculated using a ±10 ms window about the Woodford horizon. RMS amplitude attribute calculations are fast and easy to compute. Often, RMS amplitude images can differentiate high amplitude vs. low amplitude reflectivity, even when the reflectors are chaotic, with no easily picked peak or trough. Unfortunately, no significant geologic features are highlighted.

Figure 3.2 RMS amplitude map computed within a ±10 ms window about the top Woodford horizon. There is a major fault but few other features.

Figure 3.3a shows an instantaneous frequency image. An obvious transition was found in the instantaneous frequency map. Vertical section of seismic amplitude from line AA’ shows that the resolution on the left side is higher than the resolution on the right side for this Woodford layer (3.3b). Thus, this transition in instantaneous frequency map could be an indicator of thickness change or facies change.
Figure 3.3 Comparison of instantaneous frequency (a) with vertical section of seismic amplitude (b). There is a transition in the instantaneous frequency map. In vertical section of seismic amplitude, it is clear that the resolution on the left side is higher than the resolution on the right side.

A much more sophisticated and time-consuming measure of lithology is acoustic impedance. In Figure 3.4, I used a model-based acoustic impedance algorithm, which required picking a suite of horizons, tying all the well logs, kriging a background impedance model, and estimating a wavelet. Given the amount of work involved, model-
based inversion is usually not considered to be an attribute, although simpler impedance estimates using band-limited and colored inversion usually are. In general, P-impedance, S-impedance, and AVO or AVAz estimates of subsurface properties are combined with simpler attributes such as time-structure, shape, and spectral components through either visualization or through clustering, neural network, or geostatistical analysis. In this thesis I restrict myself to visualization. P-impedance removes the effect of the seismic wavelet and most tuning effects. In general, P-impedance is the ‘attribute’ most sensitive to porosity. Since there is no significant changes in porosity within the Woodford Shale cores, low porosity anomalies was interpreted to be associated with fracture porosity (Figure 2.3b).

Figure 3.4 Horizon slice along the top Woodford through a model-based acoustic impedance inversion volume. Acoustic impedance removes most of the effect of the seismic wavelet as well as thin-bed tuning effects and is more tightly coupled to impedance measures made at the wells by sonic and density logs.
Figure 3.5 Horizon slice along the top Woodford through the coherence volume. I note several other faults, what I interpret to be a collapse feature in the underlying Hunton Limestone, and a possible channel feature through the Woodford Shale.

Figure 3.6 Co-rendered image of horizon slice along the top Woodford through the coherence and acoustic impedance volumes. Note the correlation of low-impedance (yellow/green) values along some of the faults. I also note a low-impedance (yellow) value along the feature I interpreted to be a channel cutting into the Woodford shale.
In Figure 3.5 I display a horizon slice through the coherence volume. In this case, the coherence was computed by taking the ratio of the coherent energy computed using a structure-oriented KL filter to that of the unfiltered (or total energy) within a 9-trace, ±10 ms analysis window. Coherence does an excellent job of delineating the faults seen on the previous images as well as many smaller faults. I also note several circular incoherent features which I interpret to be collapse features in the underlying Hunton Limestone formation.

In Figure 3.6, I co-render the previous two images using transparency. I note that several of the low-impedance (yellow/green) anomalies line up with the faults seen on the coherence image. I also note a low-impedance (yellow) trend following the feature we interpreted to be a channel on the coherence image.

Curvature is another attribute that can be correlated to fractures. Curvature is mathematically independent of coherence and impedance, though similar features may appear in all three attribute images due to coupling through the geology. In 2D, curvature, $k_{2D}$, is defined to be the inverse of the radius of curvature, $R$, and is positive for an anticline, negative for a syncline, and zero for a planar feature (Figure 3.7a). Curvature is computed as

$$k_{2D} = \frac{1}{R} = \frac{d\theta}{ds} = \frac{dx}{ds} \frac{d}{dx} \left[ \tan^{-1}\left( \frac{dz}{dx} \right) \right] = \frac{d^2z}{dx^2} \left[ \frac{1}{1 + \left( \frac{dz}{dx} \right)^2} \right]^{3/2} \tag{1}$$

Where $\theta$ is the angle of the normal from the horizontal, $z$ is the elevation, $x$ is the lateral position, and $s$ is the length along the irregular surface. In 3D, we have two perpendicular components of curvature, which I illustrate through the use of an American football
(Figure 3.7b). The maximum curvature at a point, $P$, has the shortest while the minimum curvature has the longest radius of curvature of the football measured at any observation point. Apparent curvatures are those along any other direction and can be computed from the principal curvatures using Euler’s formula (Richards, 2001).

Figure 3.7 (a) Photo of an outcrop in Lago de Argentina illustrating curvature of a picked horizon (yellow dotted line). The curvature, $k$, is the reciprocal of the radius of curvature, $R$. (b) Definition of the curvature at a point on the surface of an American football.

Figures 3.8 to 3.11 show horizon slices through moderate and long-wavelength volumes of the most-positive and most-negative principal curvatures. In many fracture plays (e.g. Schnerk and Madeen, 2000), large through-going faults seen on curvatures
should be avoided since they may connect to underlying or overlying aquifers, while more subtle natural fractures associated with local bed folding may be confined to the formation of interest. I note that the preferable curvature images from the moderate wavelength computation bring out the definition of subtle faults and fracture lineaments that are helpful to the placement of horizontal wells. The up-thrown sides of subtle faults appear as ridges (red in most-positive principal curvature) and down-thrown sides of subtle faults appear as valleys (blue in most-negative principal curvature). The channel shows as a structural high, implying that it is perhaps sand-filled and has undergone less differential compaction than the surrounding shale.

Figure 3.8 Horizon slice along the top Woodford through the most-positive principal curvature ($k_1$) volume. Upthrown sides of subtle faults appear as ridges (red). The channel shows as a structural high, implying that it is sand-filled and has undergone less differential compaction than the surrounding shale.
Figure 3.9 The same slice shown in the previous image, but now with a longer wavelength computation of curvature, showing the broader features.

Figure 3.10 Horizon slice along the top Woodford through the most-negative principal curvature ($k_2$) volume. Downthrown sides of subtle faults appear as valleys (blue).
Figure 3.11 The same slice shown in the previous image, but now with a longer wavelength computation of curvature, showing the broader features.

Principal components of curvature $k_1$ and $k_2$ can be combined to generate shape index and curvedness which were usually developed for terrain analysis. The shape index of 3D quadratic shapes is defined as:

$$s = -\frac{2}{\pi} \text{ATAN} \left( \frac{k_2 + k_1}{k_2 - k_1} \right)$$

(2)

Where $k_1$ is most-positive principal curvature and $k_2$ is most-negative principal curvature. By definition, $k_1$ is not smaller than $k_2$. From the equation, if the shape index, $s$, equals $-1.0$, I have a bowl. If $s = -0.5$, I have a syncline. If $s = 0.0$, I have a saddle. If $s = +0.5$, I have an anticline, and if $s = +1.0$, I have a dome. If both $k_1$ and $k_2$ are equal to zero, I have a plane. The curvedness, $c$, is defined by:

$$c = [k_1^2 + k_2^2]^{1/2}$$

(3)
Very small curved features close to being in a plane are displayed as white color, and strongly curved geological features are displayed as five other colors, thereby allowing us to differentiate between reflector shapes. In visualization, we usually display shape index and curvedness together using a 2D color bar (Figure 3.12b). Interpretation of different structures based on shape index and curvedness can help us to build an appropriate tectonic deformation model, and predict fractures initiated at the time of deformation. Figure 3.13 shows the structural shape-index modulated by curvedness co-rendered with coherence. I note the continuity of a ridge shape consistent with a fault lineament indicated by coherence image in the vertical section.

We can also compute the strike of the two principle curvature, which I note as $\psi_1$ and $\psi_2$. The positive values of $k_1$ can be used to modulate $\psi_1$, and the negative value of $k_2$ used to modulate $\psi_2$ (Guo et al., 2008) giving us the image in Figure 3.14.

Figure 3.12 (a) Different shapes including bowl, valley, saddle, plane, ridge, and dome. (Courtesy of Ha Mai) (b) A 2D color table that displays the shape index versus curvedness. (After Al-Dossary and Marfurt, 2006)
Figure 3.13 Structural shape-index modulated by curvedness co-rendered with coherence.

Figure 3.14 Strata slice of $k_2$ vs. $k_2$ strike along Woodford Horizon.
Figure 3.15 Volumetric rose diagrams computed from the valley shape and axis of minimum curvature attributes extracted along the Woodford horizon co-rendered with an ‘ant-tracked’ coherence image. The boxes are the bins over which individual roses are calculated. They show very clearly two general lineament trends over the shale layer. The red color strike lines are in the NW-SE and the green color strike lines are NE-SW trend.

The amplitude and strike of the lineaments that fall within a 21 traces by 21 traces (2200ft by 2200ft) by 20 ms window can then be used to construct a volumetric rose diagram. In Figure 3.15, the rose diagram map along the Woodford Shale formation is co-rendered with an ant-tracking (Pedersen, 2002) processed coherence image. I note two clear general lineament trends over the shale layer. The fractures trend around the faults generally has NW-SE azimuth. Away from the faults there is a larger azimuth variation. Nissen et al. (2008) found that the different dominant azimuths correlated to distinct fracture sets that underwent different diagenetic alteration. Figure 3.16 is a zoomed image from the north part of the survey (Marked by a blue rectangle in Figure 3.15) indicating
that the orientation of fracture lineaments is fairly consistent vertically for the whole formation.

Figure 3.16 Rose diagram strata slice overlying on $k_2$ most-negative principle curvature from the small high producing area marked by rectangle in Figure 3.15. Note the consistency of the azimuths from the top to the bottom of the Woodford formation. The location of several high production wells correlate well with negative curvature.

Structural curvature of a picked horizon is computed from second derivatives of an interpreted time-structure map. Volumetric structural curvature is quite similar, but is computed from the first derivatives of the volumetric inline and crossline dip components, thereby circumventing the need to pick any horizons. We can also compute second derivatives of acoustic impedance, which I will call the most negative energy curvature of impedance. Figure 3.17 shows the volumetric curvature computation workflow. I note that the structural curvature is totally different from energy curvature mathematically. Figure 3.18 shows the most-negative curvature of the impedance image previously shown in Figure 3.4. There is a strong correlation seen in Figure 3.19 between
lows in the most-negative curvature of impedance image, and the structural lows shown in Figure 3.10. This correlation is consistent with fracture sweet spots associated with flexures that have lower impedance, or alternatively fractures that either give rise to an overlying stress release and velocity push-down, or enhance digenetic alteration and structural lows. Hence, coherence, structural curvature, and negative curvature of impedance are mathematically independent but coupled through the geology. I do not feel the low impedance anomalies are due to the limitations of seismic imaging about faults (Mark et al., 2010) since the fault offset is imperceptible on the vertical seismic amplitude data (Figure 3.8-3.11). Such correlations allow me to cluster different attributes to come up with one or more geologic hypotheses that define the different measures. For the Woodford Shale under the study, our hypothesis is that all lineaments from low coherence, low impedance, and structural valley are consistent with fractured shale (Figure 3.20).

Figure 3.17 Volumetric curvature computation workflow.
Figure 3.18 Horizon slice along the top Woodford through the most-negative curvature (2nd derivative) of the acoustic impedance, highlighting low-impedance lineaments.

Figure 3.19 Co-rendered image from Figure 3.10 and Figure 3.18, Notice the close correlation between them.
3.2 Visual correlation of natural fractures with production

A fracture is a discontinuity in rocks resulting from the mechanical failure due to surrounding stress imbalance. Although a single fracture is usually beyond seismic resolution, a fracture swarm, which is a group of fractures with similar geometry, might be detectable using seismic attributes because of a change in impedance due to fluid inclusion, diagenetics, or stress release. In general, seismic attributes do not directly predict the fractures; however, they do map discontinuities, folds and flexures or changes in impedances that can be used to predict natural fractures along the interpreted horizons. For the above reasons, calibration of seismic attributes to independent production, outcrop, and the core data is critical to understand the fracture behavior in a particular study.
Figure 3.21 Horizon slices through (a) coherence, (c) $k_1$ most-positive curvature and (e) $k_2$ most-negative curvature vs. well location and production. (b), (d), and (f): close up view of the high-production area from (a), (c), and (e) respectively. The bubbles represent the gross revenue of the first 90 days of those wells. I see majority of high producing wells locates at lineaments with most-negative curvature.

With 21 wells with production data, I correlated gas and oil production against attributes in an attempt to investigate their relationship. In Figures 3.21, I project the production wells onto coherence, $k_1$ most-positive principle curvature and $k_2$ most-negative principal curvature horizon slices. I find that most high oil and gas production
wells are correlated with negative curvature anomalies. This correlation is consistent with
the former study by Hart et al. (2002) that flexures and folds in brittle rock are associated
with fracture swarms. From this visual correlation, I hypothesize that natural fracture in
Woodford Shale are more intense near structure lows, such that the most-negative
principal curvature may be a robust indicator of fracture-swarm sweet spots in Woodford
Shale. In contrast, there is no strong visual correlation between the coherence images and
production because of the low sensitivity of coherence measure to small wavelength
geologic deformation. Red and green bubbles represent gas and oil production
respectively with bubble size representing the gross revenue of the first 90 days of those
wells calculated using $4/MCF (thousand cubic feet) for gas and $80/barrel for oil.

3.3 Quantitative correlation of natural fractures with production

Although three-dimensional seismic volumetric curvature attributes provide the
opportunity to correlate subtle structural lineaments to fractures, most published
curvature analysis for fracture delineation has been qualitative. Nissen et al. (2009)
determined that fluid flow is not correlated to the curvature value seen at the well, but
rather, associated with the proximity of the well to the nearest fracture lineament. Well
log analysis of chert components indicated that fracture sets of different azimuths
experienced different diagenetic alteration, leading them to postulate that fractures at one
azimuth may be open, while those at another azimuth may be sealed, and should be
treated differently. Unfortunately, this approach suffers from two pitfalls: 1) it needs
extensive manual picking, and 2) it only accounts for the contribution of fluid flow from
the nearest lineament. Our objective is to generate a suite of 3D azimuthally-limited
“fracture intensity” volumes that can then be directly correlated to production without picking. For a specific location, all the close-by fracture-related lineaments are considered to contribute to the fluid flow.

Figure 3.22 A diagram showing the fluid flow of a well controlled by fault and fracture plane in the vicinity, $\kappa$ has a very big value in the fault or fracture plane, and has approximately zero value in non-fracture zones.

Figure 3.23 Impulse responses of (a) linear and (b) non-linear convolution operators mimicking the fluid decay of a point injector. $r_{\text{max}}$ is the user-defined value for the maximum possible distance where fluid can flow from.
Figure 3.24 Impulse responses of a set of azimuthal filters.

The diagram in Figure 3.22 shows the fluid flow at one well location. The fluid flow is approximately a function of \( \kappa/r \), \( \kappa \) is permeability and \( \kappa \) is distance from well to fracture lineament. If the joint or fracture plane is open, \( \kappa \) takes a very large value, while if it is sealed, \( \kappa \) approaches to zero. Using the theory of calculus and assuming linear systems, a fluid charged fracture would provide a response proportional to the sum of a line of equally-spaced fluid injectors along the fracture. There are several steps necessary to generate an azimuthally-limited fracture intensity map.

Figure 3.25 describes the workflow used to generate azimuthally-limited hypothesized fluid flow volumes that can be used directly to correlate with production. The impulse response of azimuth filters is shown in figure 3.24. I start by the calculation of \( k_1 \), \( k_2 \) and strikes of them. Then, I generate the skeletonized image of the user-defined
curvature ($k_1$ or $k_2$) by interactively adjusting the color bar and apply azimuthal filtering to the skeletonized image to obtain different azimuthally-limited subsets using the strike of the selected principal curvature. The final step is the convolution process, ideally mimicking the fluid decay as distance increases and the convolution operator could be linearly or non-linearly defined in figure 3.23.

Figure 3.25 The workflow for calculation of “fluid flow” based on hypothesized equally-spaced “injectors” distributed along each fracture set.

In figure 3.26, I generate 6 azimuthally-limited maps along Woodford horizon to calibrate with gas and oil production in attempt to investigate the fractures from which azimuth has major contribution to the fluid flow. These maps are the hypothesized fracture fluid flow associated with fracture-related lineaments with azimuth of (a) -90°, (b) -60°, (c) -30°, (d) 0°, (e) 30°, and (f) 60°, generated from most-negative principal $k_2$
curvature and strike of $k_2$. Figure 3.27 are the corresponding close up views of the high producing areas from figure 3.26. These results show that the fluid flow is strongly correlated with the fractures, which might be open, in the NE direction because of the big correlation of production and the hypothesized fracture fluid flow from azimuth $30^\circ$ in (e) and $60^\circ$ in (f). Figure 3.28 shows spreadsheet for calculation of cross-correlation coefficient, and the bar plot giving the cross-correlation coefficient as a function of azimuth. In order to correlate the fluid flow with production more accurate, the whole survey has been split into two parts according to the fault in the north and the cross correlation was done separately for the north part (Figure 3.28a) and the south part (Figure 3.28b).

Figure 3.26 Horizon slices along Woodford showing the hypothesized fracture fluid flow from azimuths (a) -90°, (b) -60°, (c) -30°, (d) 0°, (e) 30°, and (f) 60° computed from $k_2$ most negative principal curvature and $k_2$ strike. The bubbles represent the gross revenue of the first 90 days of those wells.
Figure 3.27 Close up images showing the hypothesized fracture fluid flow from azimuths (a) -90°, (b) -60°, (c) -30°, (d) 0°, (e) 30°, and (f) 60° computed from \( k_2 \) most negative principal curvature and \( k_2 \) strike. The bubbles represent the gross revenue of the first 90 days of those wells.
Figure 3.28 Correlation of hypothesized fluid flow from different azimuth to the gross revenue of first 90 days of the wells calculated using $4/MCF (thousand cubic feet) for gas and $80/barrel for oil. (a) Cross correlation from the high producing area in the north part of the survey, (b) cross correlation from the south part of the survey. Fractures in NE direction tend to have more contribution to the fluid flow.

3.4 Visual correlation of induced fractures to volumetric attributes

In gas shale reservoirs, open natural fractures are insufficient to provide the permeability to make the reservoir economically viable. Hydraulic stimulation is the key technology developed in recent years to open healed fractures and break whole rock by injecting high pressure fluid to enhance permeability. Hydraulic fracturing of tight reservoirs triggers microseismic events resulting from the effective stress change in rocks. Passive seismic monitoring provides the location, magnitude, and sometimes the
moment of microseismic events providing an image of induced fractures that can be used to optimize the stimulation and production. The theoretical foundation for microseismic data processing and interpretation has been quite mature in recent years (Dinske et al., 2006; Drew and Calvez, 2007), and its application has been expanded tremendously (Calvez et al., 2005; Bayuk and Ammerman, 2009; Grechka et al., 2010).

In our study, the microseismicity data are collected in two wells (A and B) in the Woodford Shale during the hydraulic fracturing (Figure 3.29a). When well A serves as a treatment well, which has 6 stages, the microseismic data is recorded by monitoring well B. In the next step, the role of the two wells is exchanged, and more microseismic events are recorded (Figure 3.29b). Given a good velocity model, all the data from twelve stages are processed and the microseismic events are mapped to two way travel time for correlation with seismic data. Any individual microseismic event provides information about its source and the travel path through the rock mass from source to receiver.

![Figure 3.29 Two hydraulic fracturing wells along Woodford Shale layer generating microseismic events (a), and both well A and B have 6 stages (b). Different colors of events represent different stages.](image_url)
Figure 3.30 Microseismic event plotted with acoustic impedance from a small acoustic impedance subvolume. (a) Microseismic events from two hydraulic fracturing wells within Woodford layer. (b)-(d) Three inline sections from the acoustic impedance subvolume plotted with microseismic events. Note that, majority of events resided in the low impedance zone.
Figure 3.31 Strata slices of Woodford layer with microseismic events. (a) most negative principle curvature, (b) shape index, (c) most negative principle curvature with positive value set to be transparent, (d) shape index with ridge and dome set to be transparent.

The microseismic activity induced during the twelve fracture stages provides insight into the orientation and intensity of the induced fractures. It is important to recognize that not all induced fractures are mapped by microseismic experiments. Small magnitude events fall below the signal-to-noise threshold. More important, other fractures simply behave aseismically, which is indicated when the first event is mapped far from the injection well. In Figures 3.30 and 3.31, I project the cloud of the available microseismic events onto seismic volume attributes in an attempt to understand the fracability of the rocks in Woodford Shale. In Figure 3.30a, I display microseismic events from two hydraulic fracturing wells within a small subvolume about the wells. Figures 3.30b-d is AI images from three inline sections 1-3 respectively (Figure 3.30a) with
miscroseismic events overlain in front. Clearly, the major population of the microseismic clouds, where induced fractures reside, locates at the proximity of the low impedance anomalies. Regarding that the Microseismic data was acquired before the 3D seismic survey was shot, the low impedance anomalies may caused by the induced fracture. I also note an impedance change along the vertical direction in the Woodford layer, the upper and lower Woodford Shale have relatively low acoustic impedance and the middle Woodford Shale has relatively high acoustic impedance. According to Cardott (2007), the lower Woodford Shale composed of quartz silt and clay. The middle Woodford Shale has a very high total organic content (TOC) showing high Gamma Ray value. The upper Woodford Shale has lowest TOC. This correlation may tell us, the acoustic impedance of the Woodford Shale under my study is closely related to the clay content. Figure 3.31a and b are the strata slices of $k_2$ most negative principle curvature and shape index of the Woodford layer with microseismic events resided in. By setting the positive value or ridge and dome shapes into transparent (Figure 3.31c and d), the majority of the microseismic events shows up. In two hydraulic fracturing wells, the well crossing the ridge and dome shapes area has denser microseismic events than the well crossing the valley and bowl shapes area. Thus, the ridge and dome shaped area are easier to be fractured. This observation may indicate that the ridge and dome related to the Paleo-zones of structure weakness.
CHAPTER 4 DISCUSSION AND CONCLUSION

In the Woodford Shale, natural fractures provide a major component of porosity and permeability. For this reason, identification of fracture lineaments is essential to drilling, allowing us to map flexures, low-impedance trends, and, with prestack data, the azimuth of the minimum and maximum horizontal stress.

In this thesis, I applied volumetric curvature to the Woodford Shale, and find that $k_1$ most positive principal curvature, $k_2$ most negative principal curvature, shape components, and curvedness consistently offer a very promising opportunity to delineate both large and small wavelength lineaments related to natural fractures. The calibration with production data shows that best-producing wells come from the vicinity of lineaments associated with negative curvature.

Besides, the fluid flow calculated from $k_2$ most negative principle curvature and strike of $k_2$ was used to correlate with the production data. I found that, the high production wells are associated well with the fluid flow from NE-SW direction.

Next, the Acoustic Impedance (AI) was derived from seismic and sonic log, and correlated to the structure lineaments given by structural curvature maps and coherence image aiming at understanding the linkage between them. I observed that majority of low impedance lineaments given by the second derivative of AI correlate to structural lows. This correlation is consistent with fracture sweet spots associated with flexures that have lower impedance, or alternatively natural fractures that either give rise to an overlying stress release and velocity push-down, or enhance diagenetic alteration and structural lows. Besides, the coherence image also illuminates the edges of some low impedance
zone. All these correlations allow us to cluster mathematically independent attributes to come up with one or more geologic hypotheses that define the different measures.

As a tight-gas, -oil reservoir, the permeability of Woodford Shale is extremely low, from zero Darcy to a few milliDarcy, making the production economically infeasible. To enhance production, hydrofracture job has to be applied to generate induced fractures to improve permeability of the shale reservoir. The hydrofracturing of the shale results in microearthquakes, and the cloud of those microearthquakes provide fairly effective means of the location and intensity of the induced fractures or fracture swarms. In my study, I calibrate the microseismic events from two hydraulic fractured wells to seismic attributes, and found that microseismic events appear to be correlated to low impedance and ridge/dome features (paleo-zones of structural weakness).

Before the end of this conclusion, I would like to point out a limitation. I found a good correlation between impedance and geological structures such as faults, folds, and flexures. However, it is hard to conclude that how much percent of the correlation between impedance and coherence or curvature is associated with real geological structure. The low impedance lineaments seen in the impedance amplitude figures could relate to faults and fractures, or the diagenetic alteration. They may also be artifacts caused by image problems. Mark et al. (2010) state that in the real-world seismic image, it is common that the amplitude has been weakly imaged.
APPENDIX

SEISMIC INVERSION ANALYSIS

Seismic inversion is a technique that has been used in industry for several decades. The early version refers only to P-impedance (acoustic impedance) inversion, and the concept of current inversion includes transforming seismic data into any other elastic parameters such as elastic impedance (EI), Lame’s parameter, Poisson’s ratio, velocity using P or shear data, and it can be acoustic or elastic inversion. The theoretic basis for inversion can be dated to Zoeppritz equation, which gave the P-wave reflection coefficient as a function of incident angle between two elastic media.

Acoustic impedance (AI) and any other physical meaningful elastic parameters obtained from seismic amplitude by inversion offer the great opportunity to make predictions about lithology and porosity. By extracting information from well logs, and removing wavelet effect, these inverted parameters exhibit very high resolution, thereby improving the ease and accuracy of interpretation.

In this project, I generate AI and EI in attempt to understand the relationship of curvature and impedance. I find a strong correlation between low-impedance lineaments and structural lineaments given by curvature. I also evaluate $\lambda \rho$ (incompressibility) and $\mu \rho$ (rigidity) cross-plot, and found $\lambda \rho$ and $\mu \rho$ may be not a promising tool to predict geo-mechanical brittleness in Woodford Shale under the study.

A1. Methodology and terminology

A1.1 Acoustic Impedance Inversion
AI inversion was introduced during the middle 1970s, which was proven to be an important physical property of rocks, and provide great aid in studying rocks. As the product of rock density and P-wave velocity, AI is a function of the lithology, porosity, and fluid types of rocks. To conclude, AI owns several advantages over seismic data:

a. Unlike seismic data, AI is not an interface property which is more geologically intuitively interpretable.

b. The effect of the band-limited wavelet makes the low frequency component of seismic data unrecoverable (Russell et al., 2006). AI inversion extracts the low and high frequency component from log data and merges them with the band-limited result from seismic data, which is crucial for interpretation. Figure A1 show the impact of low and high frequencies on resolution. By comparing the inverted AI(red) with the original impedance model (black), obviously, the band-limited inversion directly from seismic data is not accurate (Figure A1a). The inclusion of high frequency (10-500 Hz) in Figure A1b improves the resolution, and the inclusion of low frequency (0-10 Hz) in Figure A1c gives an excellent result for quantitative interpretation of rock property (Latimer, 2000).

c. AI removes the wavelet interference effect and thin-bed tuning effect by calibration with wells, which makes it easy to interpret.

d. AI reduces a significant amount of noise component by constraining the impedance to the priori model and scaling impedance to the well log.
There are several seismic inversion methods in commercial packages to derive AI from seismic data and well-logs. The most commonly used include trace integration, model-based inversion, sparse spike inversion, and geostatistical inversion. Among those methods, there is no single best one for all scenarios studies. In my study, I use model-based inversion.

For model-based inversion, a background geological model or initial model is firstly built, consistent with the seismic data, by interpolation of well logs along interpreted horizons, and then synthetic traces are generated from the model and compared with the seismic trace. If the difference is significant, the impedance model is perturbed based on some criteria, and the process is repeated iteratively till the mismatch falls blow a set threshold. The parameterization of the model-based inversion plays a key role.
role to obtain a robust solution, and many current advanced approaches takes abundant geological constraint such as stratigraphy as the input to solve a global optimization problem using $L1$ norm. This method produces a broad-band high frequency inversion by taking information from initial model, and thereby resolves thin layers better than other methods.

A1.2 Elastic Impedance (EI) Inversion

The concept of EI was firstly proposed by Connolly (1998), which was proven to be promising to give different discriminating power of lithologies and fluids than AI by combining AI and AVO inversion (Whitecombe, 2002). Conceptually, EI is a generalization of AI for any specific angle stack, and AI corresponds to EI when we invert the zero-offset stacked data. The non-normalized EI formula given by Connolly (1998) is:

$$EI(\theta) = V_p\left[ V_p^{\tan^2 \theta} V_s^{-8K\sin^2 \theta} \rho^{1-4K\sin^2 \theta} \right]$$  \hspace{1cm} (A1)

Where $V_p$ is P-wave velocity, $V_s$ is S-wave velocity, $\rho$ is density, and $\theta$ is the angle of incidence. $K$ is constant, which is the average of $V_s^2/V_p^2$ over the target zone. Since EI is a function of P-wave velocity, S-wave velocity, density, and angle of incidence, it sometimes shows the higher sensitivity to the fluid change in rocks than AI. Although EI is rarely used in studying shale gas reservoir before, I anticipate that EI gives different prediction of the fracture-prone zones than AI in the survey under my study.

A1.3 Lambda Rho Vs. Mu Rho

Since late 1980, AVO inversion has been used extensively in conventional reservoir study, and numerous case studies have proven that the elastic parameters like
Poisson’s ratio and fluid factor derived from AVO can be served to predict the distribution of lithology and fluid. However, the study of tight gas resources based on AVO is quite rare till Goodway (1996; 1997) pointed out that Lambda Rho ($\lambda \rho$) and Mu Rho ($\mu \rho$) can effectively used to predict geo-mechanical brittleness in the Barnett Shale. In his papers, he claimed that $\lambda \rho$ and $\mu \rho$ cross-plot shows higher sensitivity to geo-mechanical property than the cross-plot from other parameters combination.

Grieser and Bray (SPE 2007) defined the brittleness index of shale reservoir as:

\[
\begin{align*}
E_{\text{brittle}} &= \left( \frac{E - E_{\text{min}}}{E_{\text{max}} - E_{\text{min}}} \right) \times 100 \\
v_{\text{brittle}} &= \left( \frac{v - v_{\text{max}}}{v_{\text{min}} - v_{\text{max}}} \right) \times 100 \\
\text{Brittleness} &= \frac{(E_{\text{brittle}} + v_{\text{brittle}})}{2}
\end{align*}
\]

(A2)

Where, $E$ is Young’s modulus and $v$ is Poisson’s Ratio. They suggested using the cross-plot in Figure A2 to separate geo-mechanical brittle zone and ductile zone, where low Poisson’s Ratio and high Young’s Modulus correspond to brittle zone, while high Poisson’s Ratio and low Young’s Modulus correspond to ductile zone. The study for the Barnett Shale by Grigg (2004) and Goodway (2007) is conformed to the above observation.

Since seismically intuitive parameters $\lambda$ (incompressibility) and $\mu$ (rigidity) can be derived directly using Young’s modulus and Poisson’s Ratio. The above conclusion can be extended to predict geo-mechanical properties using $\lambda \rho$ and $\mu \rho$ cross-plot. The relationship of the four parameters for the Barnett Shale is illustrated in Figure A3. From Figure A3, we observed that, geo-mechanical brittleness for the Barnett shale has
relatively low $\lambda$ and high $\mu$. Especially, $\mu$ shows a very high sensitivity to the breakout of the brittle and ductile zones.

Figure A2 The cross-plot of Poisson’s Ratio and Young’s Modulus showing the breakout of geo-mechanical brittle and ductile zones. (Grieser and Bray, 2007)

Figure A3 The relationship of Lambda, Young’s Modulus, and Poisson’s Ratio showing ductile and brittle zones. (Grigg, SPE 2004)
A2. Inverted results interpretation

Figure A4 Well log and seismic correlation showing that the correlation coefficient is 0.943 in the analysis window (between yellow lines), wavelet was generated using well. Blue traces represent the synthetic traces generated from the well logs and the wavelet. Red traces represent the 5 times repeated center trace closest to the well. The black traces represent the real seismic traces around the well.

Figure A5 Inversion analysis showing that the original log and the inversed result are pretty similar. Red traces are synthetic traces and the black traces are seismic traces.
Figure A6 Horizon slices along the top of Woodford through (a) AI, and (b) AI co-rendered with ant-tracked most-negative principal curvature. Note the strong correlation between low-impedance anomalies and the presence of curvature anomalies.

Figure A7 Horizon slices along the top of Woodford through $k_1$ most positive energy curvature and $k_2$ most negative energy curvature. (a) and (c) are $k_1, k_2$ from AI. (c) and (d) are $k_1, k_2$ from EI. The curvature from AI and EI looks very similar but the curvature from EI provides a little bit more lineaments than curvature from AI.
Figure A8 AI-EI cross plots. (a) AI–EI color plotted by lithology, and (b) AI–EI color plotted by porosity. (c) Porosity log plotted with lithology (color).

Figure A9 λρ-μρ cross plots. (a) λρ-μρ color plotted by lithology, and (b) λρ-μρ color plotted by porosity. (c) Porosity log plotted with lithology (color).
Figure A10 (a) $\lambda_\rho - \mu_\rho$ cross plot of Woodford layer. Color represents porosity. (b) Porosity log of Woodford layer.

Figure A8 and A9 shows the AI-EI cross plot and $\lambda_\rho - \mu_\rho$ cross plot from log data. I found that both AI-EI cross plot and $\lambda_\rho - \mu_\rho$ cross plot did a good job in separating different rocks because the porosity of Sandstone, Shale and Limestone are very different (indicated by Figure A8c and Figure A9c). Figure A10 is the $\lambda_\rho - \mu_\rho$ cross plot from the Woodford layer. It shows high sensitivity of the $\mu$ to the porosity.
REFERENCE


Grigg M., 2004, Gas Shale technology exchange: SPE.


