Seismic attribute-assisted interpretation of channel geometries and infill lithology: A case study of Anadarko Basin Red Fork channels.

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Summary

Detection of channels and their infill lithology has always posed a challenge for exploration geologists and geophysicists, and the Red Fork channels in the Anadarko Basin do not fall outside of this challenge. The goal of this study is to take a new look at seismic attributes given the considerable well control that has been acquired during the past decade. By using this well understood reservoir as a natural laboratory, we calibrate the response of various attributes to a well-understood fluvial system. The extensive drilling program shows that seismic data has difficulty in distinguishing shale filled channels vs. sand-filled channels, where the ultimate exploration goal is to find sand-filled channels. Furthermore, the drill bit has encountered many seismically 'invisible channels' that are of economic value. Since original work done in 1998 both seismic attributes and seismic geomorphology have undergone rapid advancement. The findings of this work will be applicable to nearby active areas as well as other intervals in the area that exhibit the same challenge such as the Springer channels.

Introduction

Since their development in the mid 1990s, coherence, spectral decomposition, and geometric attributes in general have been widely applied to mapping stratigraphic depositional environments. The paper by Peyton et al. (1998) is a benchmark not only because it perhaps is the first to demonstrate the value of spectral decomposition in mapping channels, but also because it was applied to a more difficult, lower-quality seismic survey acquired over faster Mississippian-Pennsylvanian objectives in the Mid-continent of the United States.

In 1998, Chesapeake acquired many of Amoco's Mid-continent properties including those discussed by Peyton et al. (1998). Figure 1 shows an outline of three surveys that have been merged into one single 136 sq. mi. dataset constituting the study area.

While Peyton et al.'s (1998) attribute images were excellent, they did not answer many of the key exploration questions. Specifically, can more subtle levees, fans, and overbank deposits that form part of a fluvial-deltaic system be delineated? Can sand-filled channels be differentiated from those filled by a shale plug? Is there a correlation between the cutbank of the meander belt, and thicker sands?

To address these questions we present alternative seismic attribute-assisted interpretation workflows that show the potential information that each of the geometric and amplitude-based attributes offer to the interpreter when dealing with Red Fork channels in the Anadarko Basin. It is important to mention that one of the biggest challenges of this dataset is the acquisition footprint, which contaminates the data and limits the resolution of some of the seismic attributes.

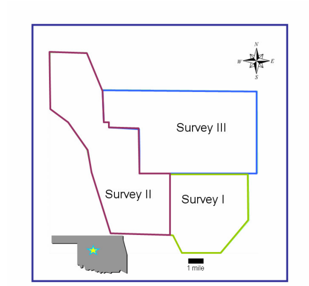


Figure 1. The surveys are located in west central Oklahoma. They were shot by Amoco from 1993-1996 and later merged into a 136 sq.mi. survey.

Method

Seismic attribute analysis.

Seismic attributes have undergone rapid development since the mid 1990s. En lieu of the horizon-based spectral decomposition based on the discrete Fourier transform, we use volumetric-based spectral decomposition based on matched pursuit and wavelet transforms (e.g. Liu and Marfurt,2007) . Other edge-sensitive attributes include more modern implementations of coherence, long-wavelength Sobel filters, and amplitude gradients. Figure 2 shows a horizon slice at the Red Fork level. Note that on conventional data the channel complex is identifiable. However, the use of seismic attributes may help delineate in more detail the different episodes within the same fluvial system and better define channel geomorphology.

We will compare different edge detection algorithms and the advantages and disadvantages that each of them provides to the interpreter. Also, matching pursuit spectral decomposition results will be presented as well as combinations of Relative Acoustic Impedance and semblance that provide helpful information in the interpretation of this dataset.

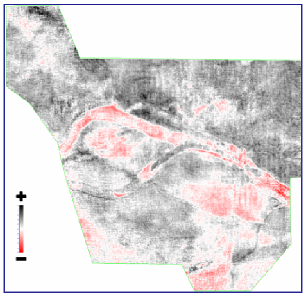


Figure 2. Conventional seismic horizon slice at the Red Fork level. The channel discernible although signal/noise ratio is affected by acquisition footprint

Coherence

According to Chopra and Marfurt (2007) coherence is a measure of similarity between waveforms or traces. Peyton et al. (1998) showed the value of this edge detection attribute to identify channel boundaries in the Red Fork level. Figure 3 shows a comparison between the horizon slice shown by Peyton et al. (1998) and a modern coherence algorithm applied to the same dataset. Note that the results are comparable. The level of detail of the modern coherence algorithm is slightly superior. It shows additional features (blue arrows), and enhances the channel levee (pink arrow).

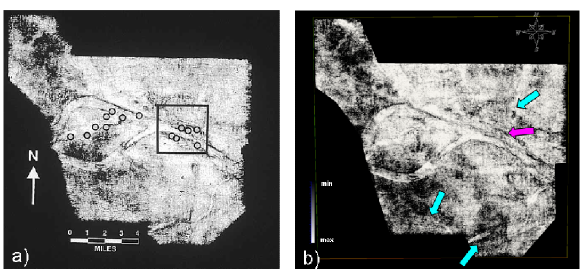


Figure 3. Coherence horizon slices at the Red Fork level. (a) Peyton et al. (1998) (b) More modern coherence algorithm. Note that the two results are comparable. However (b) shows additional features highlighted by the blue arrows and the channel levee highlighted by the pink arrow.

Energy Weighted Coherent Amplitude Gradients

Chopra and Marfurt (2007), by using a wedge model, demonstrate that waveform difference detection algorithms are insensitive to waveform changes below tuning frequencies. In this study the *energy ratio coherence*, defined by the coherent energy normalized by the total energy of the traces within the calculation window, and the *Sobel coherence,* which is a measure of relative changes in amplitude were used. They aided the detection of subtle changes in amplitude packages that may be correlated to facies boundaries within the fluvial system.

Figure 4 shows a horizon slice of the energy ratio coherence and the Sobel coherence at the Red Fork level. The results from these two energy weighted routines are very similar to the coherence attribute, but greater detail. This can be seen in the smaller channel located northeast of the main channel complex system (yellow arrow), and in the meandering channel located in the southeast corner of the survey (pink arrow). Also, the cut-bank of the channel (blue arrow) has less coherent energy than the gradational inner-bank (green arrow). Even though both algorithms show similar features, the Sobel coherence seems to be more affected by the acquisition footprint than does the energy ratio coherence.

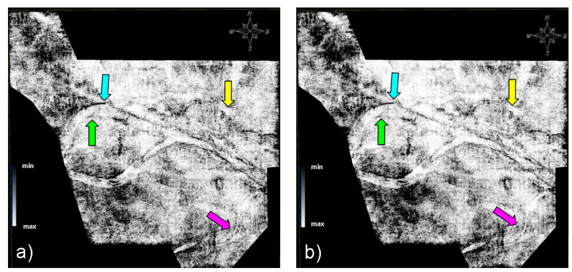


Figure 4. Other modern edge-detector attributes: a) Sobel coherence. b) Energy ratio coherence. The two algorithms show a slightly higher level of detail compared to the conventional coherence. The Sobel coherence seems to be more sensitive to acquisition footprint.

Spectral Decomposition

Matching pursuit spectral decomposition was used to generate individual frequency volumes as well as peak amplitude and peak frequency datasets. Peyton et al. (1998) shows the usefulness of spectral decomposition for facies discrimination in the Red Fork channel system. Figure 5a shows Peyton et al.'s (1998) discrete Fourier transform (DFT) 36 Hz spectral decomposition Red Fork horizon slice.

Castagna et al. (2003) discuss the value of using matching pursuit spectral decomposition and how we can associate different "tuning frequencies" to different reservoir properties like fluid content, thickness and/or lithology. Figure 5b shows a matching pursuit 36 Hz spectral component at the Red Fork level. The level of detail using matching pursuit spectral decomposition is superior to that provided by the DFT. The enhanced results may be related to the fact that the matching pursuit spectral decomposition is a least-squares algorithm while the (nonorthogonal) DFT algorithm is a simple project algorithm that can somewhat smear the results. Cyan arrows highlight areas of increased detail. Note the better definition of the channel-levee features and crisper channel boundaries in the overall system.

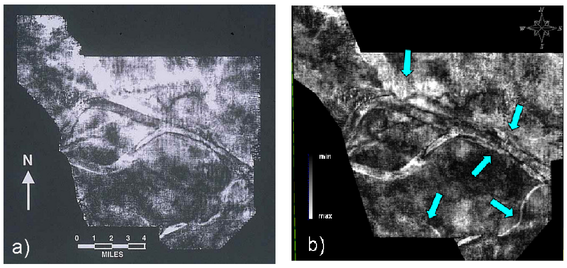
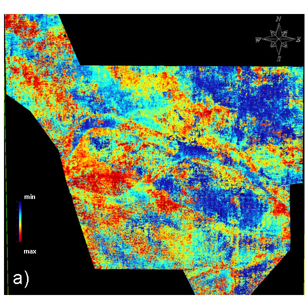


Figure 5. Spectral Decomposition horizon slice at the Red Fork level. (a) 36 Hz DFT spectral decomposition from Peyton et al. (1998). (b) 36 Hz matching pursuit spectral decomposition. Note the enhanced level of detail offered by the matching pursuit spectral decomposition.

Peak Frequency and Peak Amplitude Displays

Even though spectral decomposition offers an excellent tool to aid fluvial system interpretation, it is well known that efficiently managing these multiple volumes of data to extract their relevant information is a challenge for the interpreter. Liu and Marfurt (2007) show that by combining the peak frequency and peak amplitude volumes extracted from the spectral decomposition analysis, the interpreter can identify highly tuned channels. Low peak frequency values correlate with thicker intervals and high peak frequencies with thinner features.

Figures 6a and b show the peak amplitude and peak frequency volumes respectively. Figure 6c shows the combination of both displays, which simplifies the interpretation of multiple volumes of data. The well locations highlighted in the picture are Red Fork producers. The sand thicknesses within the channel varies from 20'-140'. By combining the information from well data and the peak spectral attributes, we concluded that the lower peak frequency values within the main channel complex are correlative to shalier channel infill lithology (green arrow). Outside of the channel complex the lithology relationship with frequency is still unclear.



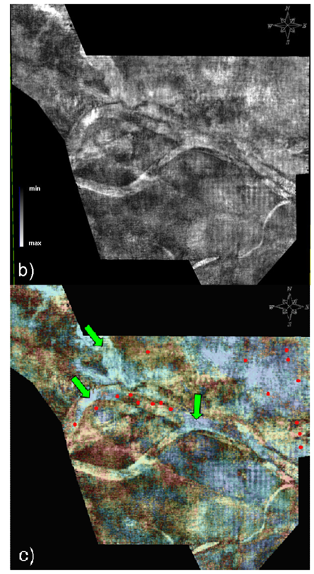


Figure 6. Peak Frequency and Peak Amplitude analysis at the Red Fork level. (a) Peak Frequency volume, red corresponds to higher frequencies. (b) Peak Amplitude volume, white corresponds to higher peak amplitude values. (c) Peak frequency and peak amplitude blended volume. The co-rendered image shows channel boundaries and potential channel thickness changes that can be correlated to peak frequency values. Note that lower peak frequency values within the main channel complex may be correlative to shalier channel infill lithology.

Curvature

Although successful in delineating channels in Mesozoic rocks in Alberta, Canada (Chopra and Marfurt, 2008), for this study, volumetric curvature does not provide images of additional interpretational value. While the Red Fork channel boundaries can be delineated using this attribute (Figure 7), the results shown by the coherence and spectral decomposition are superior. In this situation the acquisition footprint negatively impacts the lateral resolution quality of the attribute.

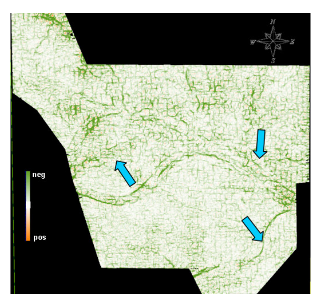


Figure 7. Most negative curvature at the Red Fork level. Note how the footprint challenges the edge detection capabilities of this attribute. Blue arrows indicate channel edges.

Relative Acoustic Impedance

The Relative Acoustic Impedance (RAI) is a simplified inversion. This attribute is widely used for lithology discrimination and as a thickness variation indicator. Since the RAI enhances impedance contrast boundaries, it may help delimit different facies within a fluvial complex. Figure 8 shows the better delineation of channels provided by RAI. The impedance amplitude variations within the channel complex may be correlated to sand/shale ratios. Higher values of RAI seem to be related to shalier intervals inside the body of the channel (black arrow).

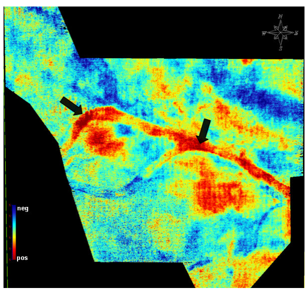


Figure 8. Relative Acoustic Impedance (RAI) at the Red Fork level. Since RAI enhances impedance contrast boundaries, changes in lithology are more evident.

Semblance of the Relative Acoustic Impedance

Chopra and Marfurt (2007) define semblance as "the ratio of the energy of the average trace to the average energy of all the traces along a specified dip." Since RAI has sharper facies boundaries the semblance computed from RAI should be crisper than semblance computed from the conventional seismic. Figure 9 shows the value of combining these attributes.

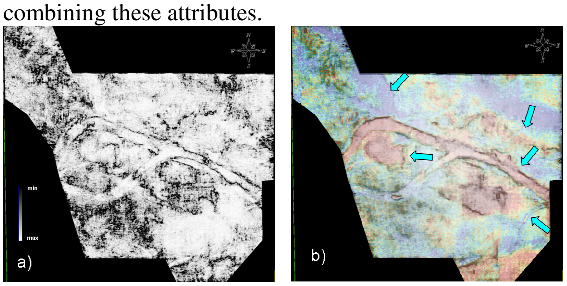


Figure 9 a) the Semblance of the RAI and b) RAI and RAI semblance blended image. The combination of both attributes helps delineate Relative Acoustic Impedance boundaries. Compare to Figures 3 and 4.

Conclusions

This study has identified correlations between attribute expressions of Red Fork channels that can be applied to underexploited exploration areas in the Mid-continent, and to fluvial deltaic channels in Paleozoic rocks in general.

When it comes to answer the key questions discussed at the beginning of this paper, we learned that the curvature and energy weighted attributes help improve the resolution of subtle features like small channels and channel levees. They also help differentiate the cutbank from the gradational inner bank. It is also evident from this study that even though there have been some improvements in the coherence routines, the differences between current algorithms with the ones applied by Peyton et al. in 1998 are minimal.

Additionally, detailed channel geomorphology and lithology discrimination were possible by introducing the spectral decomposition and relative acoustic impedance attributes in the analysis. On one hand, the use of spectral decomposition helped define different facies within the channel system and increased the resolution of channel boundaries. On the other hand, the variations in the RAI values were found to be correlative to lithology infill, for instance higher values of RAI show direct relationship to shalier intervals within the channel complex.

One of the key findings of this study is the great value that blended images of attributes bring to the interpreter. Such technology was not available ten years ago. But today, by combining multiple attributes, fluvial facies delineation is possible when co-rendering edge detection attributes with lithology indicators.

It is important to mention that the signal/noise ratio of the data is a key factor that will determine the resolution and quality of the seismic attribute response. In this study, curvature did not provide images of additional interpretational value. These unsatisfactory results may be related to acquisition footprint contamination. Therefore, footprint removal methods will be performed in an attempt to enhance signal-to-noise ratio.

Acknowledgments

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