The Integrated Use of Spectral Decomposition, AVO Analysis, Seismic Attributes, Principal Component, Supervised Neural Facies Classification, and Waveform Calibration for Reservoir Delineation: Examples from Western Canada

Joseph Chow*
Kelman Technologies Inc, Calgary, AB
josephc@kelman.com

George Gluszak
Orleans Energy Ltd, Calgary, AB, Canada

and

Paul Chernoff and Rob Tilson
Kelman Technologies Inc, Calgary, AB

Summary

In this study, spectral decomposition, AVO analysis, seismic attributes, principal component analysis, supervised neural facies classification and waveform calibration were combined to delineate potential hydrocarbon bearing zones in plays from Western Canada.

Introduction

Various reservoir characterization methods have been used over the years to reduce the uncertainties associated with identifying potential hydrocarbon reservoirs. For example, spectral decomposition (e.g. Partyka et al., 1999) and AVO Analysis (e.g. Castagna and Swan, 1997) are popular techniques. These methods may be augmented with principal component analysis and neural network facies classification to further analyze hydrocarbon potential. Principal component analysis was used in these data sets to study the relationships, represented by the correlation matrix, that exists among given attributes.

Method

Some publishable data of several 3D surveys in Western Canada were examined in this paper. For carbonate environments, several attributes were extracted, including relative acoustic impedance, semblance (coherence), Avo attributes, waveform difference, simple difference, instantaneous amplitude, frequency, and Q, positive and negative curvatures, strike and dip curvatures, and Lambertian reflectance. For clastic environments, the attributes used were relative acoustic impedance, volume curvature, AVO attributes, semblance, waveform difference, simple difference, instantaneous amplitude, instantaneous frequency, instantaneous Q, and apparent polarity. For fractured reservoirs, we chose semblance (coherence), Avo attributes, Gaussian curvature, postive and negative curvatures, strike and dip curvatures, contour curvature, curvedness, Lambertian reflectance and throw. The method used was as follows. A stratigraphic cube was created for each attribute. Spectral Decomposition Analysis was then applied on each cube to determine reservoir morphology and reservoir characterization. Morphologies such as reefs, channels, fans and point bars were determined. Principle Component Analysis was then applied on chosen cube attributes to identify, for example, the dolomite distribution within a reef, channel edges and potentially porous point bars. Neural network facies classification was then used to extract and quantify multi-attribute patterns for reservoir delineation.

Examples

In Figures 1a) and 1b), spectral decomposition was used to identify erosional remnants of thin reservoirs in a meandering channel system, by breaking down the seismic signal into its frequency components. In this case, the frequency cube was 45 Hz.

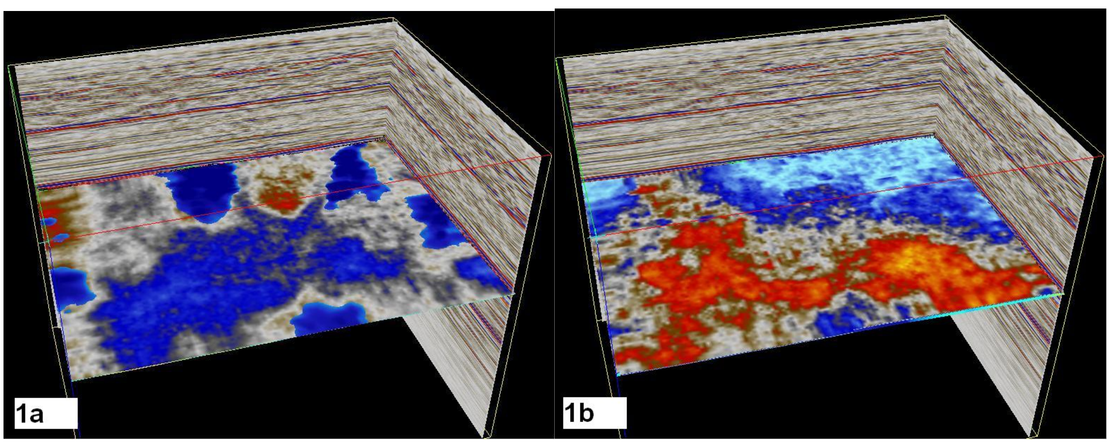

Figure 1: Channel sands play: (a) Conventional amplitude slice of the productive interval does not detect the thin channel reservoir; (b) Spectral decomposition reveals the thin channel reservoir.

Figures 2a) and 2b) show the results of curvature Analysis. Curvature computation removes the effects of regional dip, thus emphasizing small-scale features that cannot be observed on conventional data, including reefs, fractures and small faults. In this case, the fractured reservoirs are easily delineated.

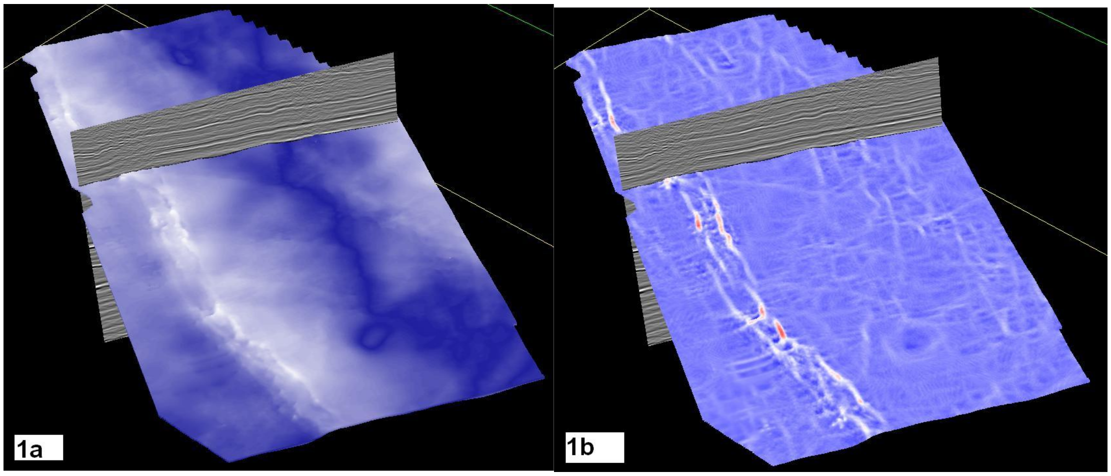

Figure 2: Fractured reservoirs: (a) Conventional seismic data does not detect small-scale structural and stratigraphic features; (b) Image from curvature computation identifies small-scale faults and fractures.

AVO intercept and gradient attributes were extracted from the linear regression of pre-stack seismic data. Lithology, rock properties were determined from the intercept/gradient crossplot. By combining attribute Analysis, AVO attribute analysis, principal component analysis and supervised facies classification, we can predict hydrocarbon reservoirs, which were confirmed later by well data.

In a specific area of Western Canada, dolomitized zones of a 3D data generated by this method shows that every successful well is drilled into the dolomitized zones, while all the dry wells are located at the non-dolomite zones. Since the results of the dolomitized zones are still confidential, we are not able to display it in this abstarct, but we hope one day it can be published.

Conclusions

Spectral decomposition analysis, AVO analysis, multiple attributes analysis, principal component analysis, supervised neural facies classification, and waveform calibration successfully delineate reservoirs with hydrocarbon potential.

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References

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