Reservoir Characterization using 3-D Seismic Data in BlackGold Oilsands Lease, Alberta Canada

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Abstract: Reservoir Characterization (RC) using 3-D seismic attributes analysis can provide properties of the oil sand reservoirs, beyond seismic resolution. For example, distributions and temporal bed thicknesses of reservoirs could be characterized by Spectral Decomposition (SD) and additional seismic attributes such as wavelet classification.

To extract physical properties of the reservoirs, we applied 3-D seismic attributes analysis to the oil sand reservoirs in McMurray formation, in BlackGold Oilsands Lease, Alberta Canada. Because of high viscosity of the bitumen, Enhanced Oil Recovery (EOR) technology will be necessarily applied to produce the bitumen in a steam chamber generated by Steam Assisted Gravity Drainage (SAGD). To optimize the application of SAGD, it is critical to identify the distributions and thicknesses of the channel sand reservoirs and shale barriers in the promising areas.

By 3-D seismic attributes analysis, we could understand the expected paleo-channel and characteristics of the reservoirs. However, further seismic analysis (e.g., elastic impedance inversion and AVO inversion) as well as geological interpretations are still required to improve the resolution and quality of RC.

Keywords: EOR, SAGD, reservoir characterization, 3-D seismic attributes analysis, spectral decomposition, wavelet classification

1. INTRODUCTION

1.1 Background to This Study

McMurray formation contains oil sand reservoirs, in BlackGold Lease, Alberta Canada. Because of high viscosity of bitumen, Enhanced Oil Recovery (EOR) technology of Steam Assisted Gravity Drainage (SAGD) will be applied to generate steam chambers to lower viscosity of the bitumen and make it producible. Since the SAGD is expensive and complicated, an optimal production technique is indispensible to maximize the production rate.

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To optimize the application of SAGD, it is critical to identify the distribution and thickness of the channel sand reservoirs and shale barriers in the promising areas (Pooladi-Darvish and Mattar, 2002), because the oil sand reservoirs in the block have relatively thin and complex depositional facies such as meandering fluvial channels. Therefore, high resolution of reservoir characterization (RC) is required to design the SAGD. However, the number of wells is more than 150 in the area of 39 km^2 in BlackGold Lease. This means that the average resolution of RC using well data only is 454 m × 454 m.

Generally, RC using only well data has a limitation on resolution. However, the resolution of RC can be improved by using additional seismic data and attributions. For example, the resolution of RC using both seismic and well data could be improved from 454 m × 454 m to 20 m × 20 m, depending on the seismic acquisition and data processing parameters in the block. We perform 3-D seismic attributes analysis for the RC to extract the properties beyond seismic resolution. For example, the distribution and thickness of the channel sand reservoirs and shale barriers in McMurray formation are characterized by SD and additional seismic attributes such as wavelet classification (Dubrule et al., 1998; Partyka et al., 1999).

1.2 Summary of the Block

BlackGold Oilsands Lease is located 140 km southeast of Fort McMurray in the Athabasca Oil Sands region of northern-eastern of Alberta, Canada (see Fig. 1) and its recoverable bitumen reserves are expected to be more than 200 million bbls. BlackGold Oilsands Lease covers 39 km^2 and KNOC (Korea National Oil Corporation) has the operatorship and 100 % of working interest of the block. We acquired BlackGold Oilsands Lease from Newmont Mining Corporation in August 2006.

Since August 2006, KNOC acquired 3-D seismic data in the area of 25 km^2 for further evaluation, where there are more than 150 wells drilled by both KNOC and former operator. Recently, we are expanding the facilities so that more than 20,000 bbls can be produced a day, which will ultimately raise our daily production rate to 30,000 bbls. This is our basic plan and target in the foreseeable future.

Fig. 1. Location Map of the BlackGold Lease Block in Alberta, Canada.

2. SPECTRAL DECOMPOSITION

SD using Gabor-Morlet complex wavelet transform, Discrete Fourier Transform (DFT), Continuous Wavelet Transform (CWT) and many other time/frequency transforms is applied to extract some meaningful information about temporal bed thickness and geological distribution from 3D seismic data. In this study, Gabor-Morlet complex wavelet transform has been used to transform 3-D time-domain seismic data to the time/frequency domain.

2.1 Gabor-Morlet Complex Wavelet Transform

Complex-valued Gabor wavelet is represented as a product of a complex sinusoidal function and a Gaussian envelope in the time domain (Gabor, 1946):

$$g_\gamma(t) = w\left(\frac{t-u}{\sigma}\right)e^{\{i[\omega(t-u)]+\phi\}}, \qquad (1)$$

where $w(t)$ is a Gaussian window, u is the time delay (translation), σ is the spread in the time axis (scale), ω is the central angular frequency (modulation), and ϕ is the phase shift. Using the Gabor wavelet, it is possible to define a seismic trace $f(t)$ as follows

$$f(t) = \sum_{n=0}^{N-1} a_n g_{\gamma_n}(t) + R^{(N)} f, \qquad (2)$$

where a_n is the amplitude of the nth wavelet $g_{\gamma n}$, $R^{(N)}f$ is the residual with $R^{(0)}f = f$.
For seismic reflection signal analysis, the complex Gabor wavelet (1), which is called Morlet wavelet, is used as a basic signal model. This Morlet wavelet is suitable for energy and frequency quantification of seismic data, and particularly appropriate for resolution studies (e.g., spectral decomposition) of acoustic waves propagating through porous media.
A Morlet wavelet $m(t)$ centered at the abscissa u can be defined as (Morlet et al. 1982a, b)

$$m(t) = e^{\left[-\left(\frac{\ln 2}{\pi^2}\right)\frac{\omega_m^2 (t-u)^2}{\sigma^2}\right]} e^{\{i[\omega_m(t-u)]+\phi\}}, \qquad (3)$$

where ω_m is the mean angular frequency, and σ is a constant value that controls the wavelet width. The Fourier transform of $m(t)$ is given by

$$M(\omega) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} e^{\left[-\left(\frac{\ln 2}{\pi^2}\right)\frac{\omega_m^2}{\sigma^2}(t-u)^2 - i(\omega-\omega_m)(t-u) - i(\omega u - \phi)\right]} dt. \qquad (4)$$

We then have an analytic expression for the time-frequency amplitude spectrum as follows

$$Af(t,\omega) = \sum_{n=0}^{N-1} \frac{a_n}{\left\| g_{\gamma_n} \right\|}\left(\sqrt{\frac{\pi}{2\ln 2}}\,\frac{\sigma_n}{\omega_n}\right)^{1/2} e^{\left[-\left(\frac{\pi^2}{4\ln 2}\right)\frac{\sigma_n^2(\omega-\omega_n)^2}{\omega_n^2}\right]} e^{\left[-\left(\frac{\ln 2}{\pi^2}\right)\frac{\omega_n^2(t-u_n)^2}{\sigma_n^2}\right]}, \qquad (5)$$

where $\omega_n \equiv \omega_{m,n}$ is the mean frequency of the nth wavelet, and $\left\| g_{\gamma_n} \right\|$ is a normalization factor (Wang, 2007).

2.2 Theory of SD

SD, which makes it possible to analyze spectral characteristics related to geological information, has been widely applied to 3D seismic survey data acquired for thin bedded reservoirs, distributed channel, turbidite and reef related plays. The main concept supporting SD is that a reflection from a (thin) bed (e.g., channel sand and shale barriers in McMurray formation) has a distinctive characteristic in the frequency domain, which indicates the temporal bed thickness. The seismic wavelet, however, typically spans multiple subsurface layers as well as one simple thin bed (see Fig. 2).

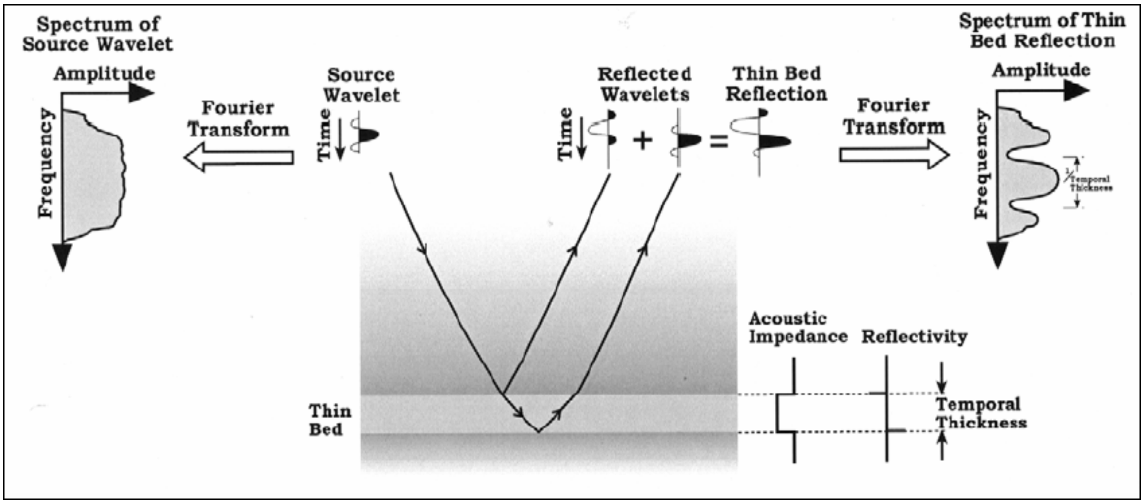

Fig. 2. Thin-bed spectral analysis (Partyka et al., 1999).

Note that amplitude spectrum of long time-windowed data is significantly different from that of short time-windowed data. Long time-windowed data yield a broad-band amplitude spectrum (e.g., “Fig. 3”), whereas amplitude spectrum of short time-windowed data represents a local interference pattern as well as the effect of the shape of wavelet from which the acoustic properties and thickness of the layers can be inferred (e.g., “Fig. 4”). With a few exceptions (e.g., cyclothems and sabkhas), the amplitude spectrum of long time-windowed data statistically results in randomized interference patterns of individual thin beds within the window. Thus, the long time-windowed data gives whitened or flattened amplitude spectrum.

Finally, the convolution of a source wavelet with a random geologic section creates an amplitude spectrum that resembles the wavelet (see Fig. 3).
Amplitude spectrum of the short time-windowed data is dependent on the acoustic property and

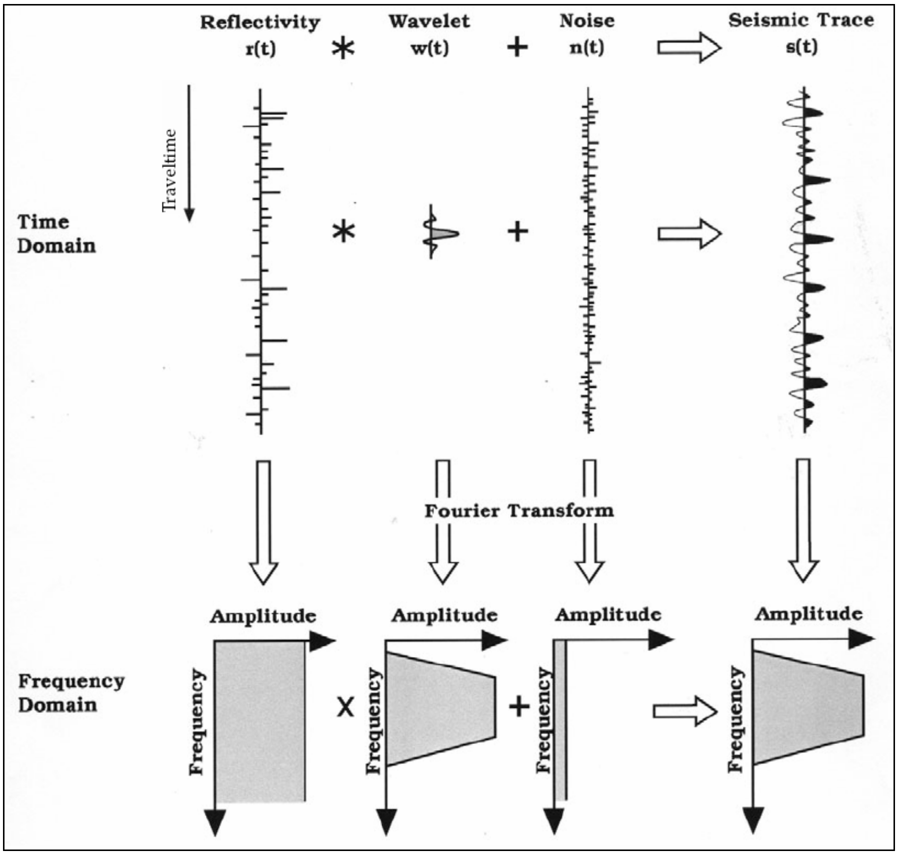

Fig. 3. Long-window spectral decomposition and its relationship to the convolutional model (Partyka et al., 1999).

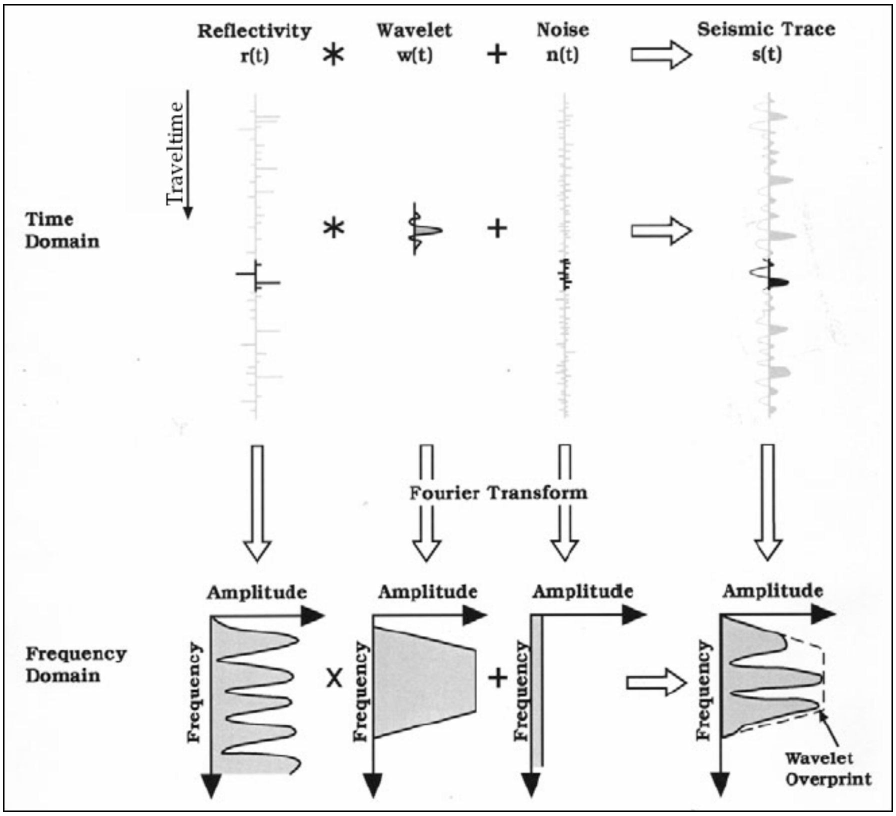

Fig. 4. Short-window spectral decomposition and its relationship to the convolutional model (Partyka et al., 1999).

thickness of the layers. In a bed, the physical properties act as a local filter on the reflecting wavelet, thereby attenuating its spectrum. The resulting amplitude spectrum is not white and represents the interference pattern within the window (see Fig. 4) (Partyka et al., 1999).

As a short time-window transform, we apply the Gabor-Morlet complex wavelet transform, which provide amplitude spectrum and phase spectrum in the time/frequency domain.

3. WAVELET CLASSIFICATION

The Neuronal method (Ornstein, 1965; Mohaghegh, 2000) is an artificial intelligence process that excels at pattern recognition. The Neuronal method can be used for all kinds of seismic data types. We use a user-defined training set to define the kernels of Facies map using neural networks (e.g., “Fig. 5”). Following three parameters are required at the processing stage using Paradigm software (Paradigm B.V., 2009).

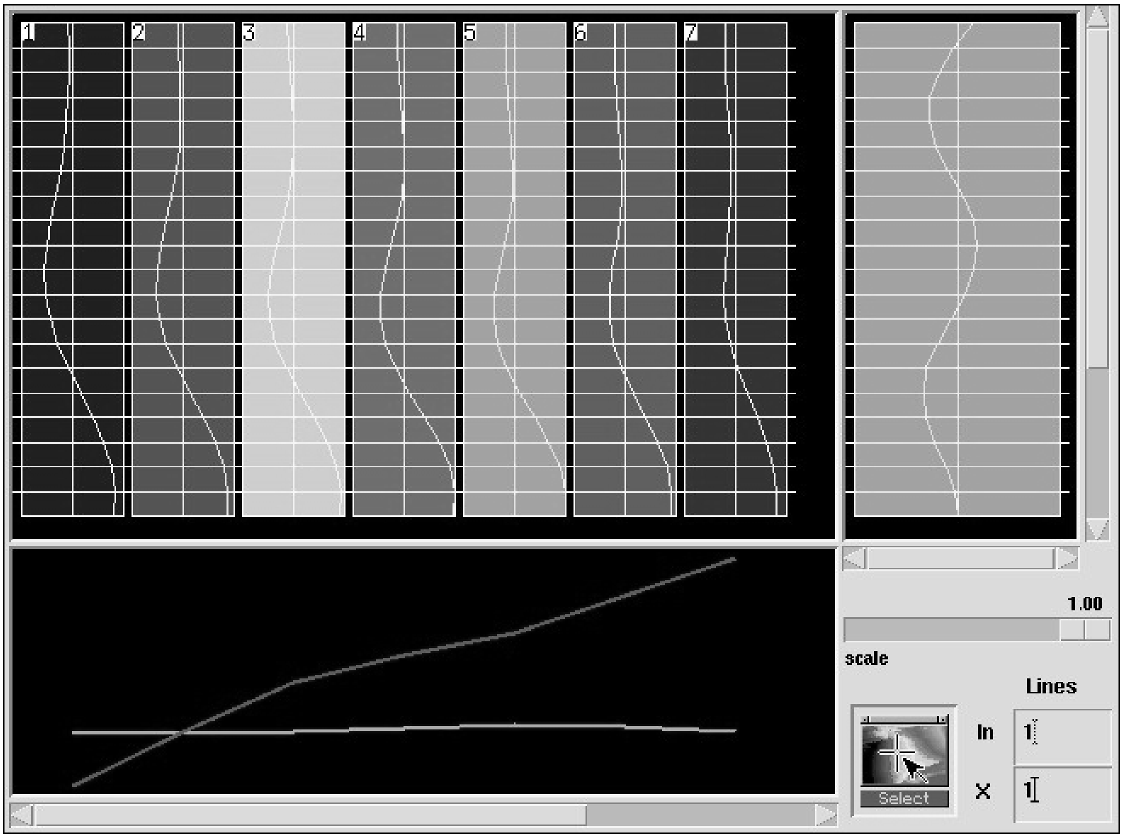

Fig. 5. Example of Classified Wavelets Displayed by Paradigm Software.

3.1 Number of Classes

The number of different trace classes or wavelets is given to be encountered over the whole survey area. Wavelet classification can generally be applied to classify geological facies on the basis of the shape or physical properties of wavelet. However, it does not provide any geological information directly.

3.2 Size of the Training Set

The X and Y dimensions are the sampling intervals. For example, X=4 means that one out of four traces will be used in X dimension.

3.3 Number of Iterations

This determines how many times the neural network should be calculated to improve the relevance of classification in relation to the data of the training set.

4. APPLICATION

To define the distributions and temporal bed thicknesses of the reservoirs and shale barriers, we applied SD and wavelet classification to the McMurray formation. The thickness of the reservoir in the McMurray formation varies from 10 m to 30 m approximately, thus, the attribute map from SD was derived for stacking frequencies ranging from 15 to 50 Hz. More specific range of stacking frequency was defined by parameter tests including the frequency range and transform.
It is important to determine which part of the trace (e.g., time window) should be used for wavelet classification. The time window can cover either the top or the bottom boundary of the formation that we are interested in. Both of them can be included in the time window. For example, when the target is McMurray formation, the time window used for wavelet classification can be designed to cover from 5 ms above the upper boundary to 5 ms below the bottom boundary of McMurray formation. Results obtained for different time windows show different characteristics. Wavelet classification can be applied to each or the combination of stacked sections, acoustic impedance volumes and other attributions.

5. CONCLUSION

We tested SD for various ranges of frequency, time and depth, and many sort of attribute analysis for this study. From the results of this study, we could confirm that the resolution of the RC can be improved by using both 3-D seismic data and well data, and we characterized the distributions and temporal bed thicknesses of the reservoirs and shale barriers. Furthermore, we also identified paleo-channel systems and the characteristics of the reservoirs using 3-D seismic data including 3-D seismic attributions. Finally, we expect that the results of this study could help us to determine the regions where we can apply SAGD or where we cannot apply SAGD.

6. DISCUSSION

Recently, AVO inversion and attributes has been applied to the oil sand reservoir in Canada (Xu and Chopra, 2008) and they show reliable results of the application. In the BlackGold area, we also have 3-D and 3-component seismic data available and it is believed that the results of RC using the AVO inversion, AVO attributes, elastic impedance inversion as well as more detailed geological interpretation of the 3-D seismic data should be better. However, handling of S-wave data requires more time and 3-D shot gather, higher computational power. For these reasons, we leave the AVO inversion, AVO attributes and elastic impedance inversion for our future studies.

7. ACKNOWLEDGMENTS

This study has been related to the current project of our company, in Canada. Therefore, it is regrettable to avoid detailed explanations and related figures. We would like to apologize for this matter to KSEG and its members.

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