Volumetric application of skewed spectra

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Summary

Spectral decomposition is a powerful analysis technique that provides direct measurement of thin-bed tuning effects. One limitation in using spectral decomposition in volumetric analysis is the shear size of the spectral component volumes that are generated. For this reason, peak amplitude, peak frequency, and peak phase, which represent the mode of the complex spectra have proven to be three of the most useful volumetric spectral attributes. While estimates of the spectral mean, bandwidth, skewness, and kurtosis have been available in commercial formation-based spectral decomposition software for almost a decade, few if any case studies have been presented showing its value. Since many spectra are bi- vs. unimodal we find the mean spectra, bandwidth and kurtosis to have only limited interpretation value. In contrast, spectral skewness estimates quantify the asymmetry of the spectra which in turn can be correlated to multimodal behaviour due to channels, as well as the presence of upward fining, and upward coarsening sequencies.

Introduction

First applied to 3D seismic volumes by Partyka et al. (1999), spectral decomposition has since become a routine interpretation analysis tool. The more common applications include identification of tuning thickness (e.g. Marfurt and Kirlin, 2001; Tirado, 2004) and direct hydrocarbon detection (Castagna et al., 2003). Unfortunately, the 4D spectral decomposition volumes obtained from 3D data are unwieldly, presenting both visualization and data management problems. For this reason, we seek to identify a small suite of 3D volumes that represent key spectral features of the 4D volume.

The most straightforward and broadly used attributes associated with spectral decomposition are peak amplitude, peak frequency, and peak phase (Liu et al., 2007; Matos and Johann, 2007). Measures of peak amplitude above the average spectrum provide added delineation of high-amplitude tuning events (Blumentritt, 2008). However, it is naive to think that one frequency can fully represent the complete spectrum.

Several commercial implementations of formation-based spectral decomposition provide measures of the spectral mean, bandwidth (proportional to the standard deviation), skewness, and kurtosis. These measures are excellent in defining moderate spectral variations away from what is otherwise a Gaussian distribution. However, we found that some of the features of most interest were bimodal, thereby violated the Gaussian assumption. Futhermore, our analysis is done after (statistical) spectral flattening (Liu and Marfurt, 2007), such that the average spectrum is by definition flat (and non-Gaussian) within the frequency-band analyzed. Nevertheless, we find skewness to be a spectral measurement that is statistically applicable to an univariate continuous spectra. A spectra is skewed if one of its tails is longer than the other. A symmetric frequency spectrum at a given time sample has zero skewness. An asymmetric spectrum with a long tail extending to the high frequency direction has a positive skewness, and vice versa.

Theoretically, skewness is sensitive to the shift of the dominant energy of the spectrum along the temporal and spatial directions of the seismic data, which enables us to map structural and stratigraphic variation on seismic time and horizon slices. Skewness is also quite sensitive to bimodal vs. unimodal spectral behavior, allowing us to map geologic features that give rise to these changes as well. For the data volume presented here, we find that channels have lower skewness than other facies, with the channels giving rise to spectra that have either bimodal behavior or low dominant frequency.

Measures of skewness

Skewness is a measure that can be used to define the degree of asymmetry of a distribution. A symmetric spectrum such as a Gaussian spectrum has zero skewness, an asymmetric spectrum with a longer high frequency tail has positive skewness, while a spectrum with a longer low frequency tail has negative skewness. The classic skewness is defined as the third standardized moment:

$$S(t) \equiv \frac{\int_{-\infty}^{+\infty} (f - \mu(t))^3 a(t,f)\,df}{b^3(t) \int_{-\infty}^{\infty} a(t,f)\,df} \quad (1)$$

where, *a(t, f)* is the spectral magnitude corresponding to time *t* and frequency *f*. *μ(t)* and *b(t)* are the mean frequency and bandwidth respectively which are defined by:

$$\mu(t) \equiv \frac{\int_{-\infty}^{+\infty} f a(t,f)\,df}{\int_{-\infty}^{\infty} a(t,f)\,df} \quad (2)$$

$$b^2(t) \equiv \frac{\int_{-\infty}^{+\infty} (f - \mu(t))^2 a(t,f)\,df}{\int_{-\infty}^{\infty} a(t,f)\,df} \quad (3)$$

Since *S(t)* may be strongly affected by outlier values, and since our data will always be band-limited, we evaluate other skewness measures and find that presented by Hinkly (1975) provides more robust skewness measures:

$$S(t) \equiv \frac{(Q_p + Q_{1-p} - 2 * Q_{0.5})}{Q_{1-p} - Q_p} \qquad (4)$$

where, Q_p is the p-th quantile of the spectrum and p varies between 0 to 1. If $p=0.25$, equation 4 defines the "quartile skewness"; if $p=0.125$, equation 4 defines the "octile skewness". An optimum value of p can be determined from the data. For our examples we use the quartile skewness.

Synthetics

Seismic frequency is a significant tool to recover stratigraphic information from qualitative analysis of seismic data, and can be used to analyze sequence features such as downlap, onlap, and toplap deposition (Zeng et al, 1998a). Since the conventional approach to study seismic stratigraphy and sedimentation cycles is based on high dimensional spectral decomposition results, the extraction of more economical and straightforward seismic attributes becomes essential. As a measure which is very sensitive to the shift of the dominant energy along the temporal and spatial dimension, skewness should provide a good indicator of upward fining and upward coarsening of the clastic depositional sequences. Figure 1 shows a suite of impedance models, synthetics and related negative skewness (red dash line on the bottom figure). The good cross-correlation between negative skewness and models of different possible stratigraphic sequences demonstrates that skewness is a potentially good attribute to map upward fining and upward coarsening features.

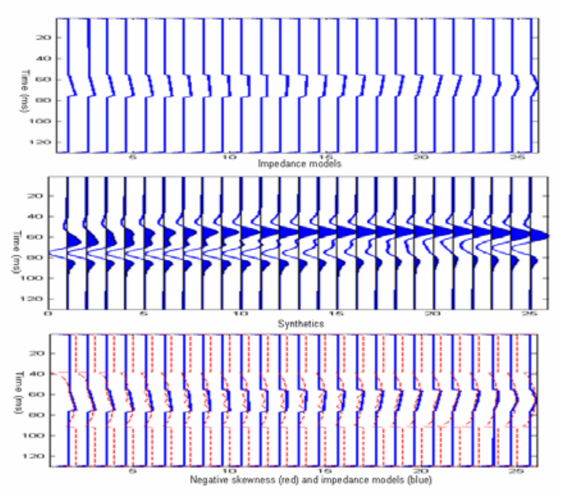

Figure 1: Impedance models (top), synthetics using Morlet wavelet, and comparison of models with red dash skewness curves (bottom).

Real data examples

The beauty of the spectral attributes such as peak amplitude, peak frequency, peak phase and now of course, skewness lie in the fact that they facilitate the seismic data interpretation by decreasing the dimension of the awkward spectral decomposition output data, yet are sensitive to features of stratigraphic interest.

Figure 2 shows a time slice at t=1.05s through a seismic amplitude volume acquired over Paleozoic channels in the Central Basin Platform, West Texas. We compute 4D spectral magnitudes and phases using a matching pursuit decomposition algorithm described by Liu (2006) based on fitting a suite of precomputed Ricker wavelets (from a dictionary) to the seismic data. The process is iterative and concludes when the residual energy is acceptable. The complex spectra of each Ricker wavelet are summed, providing an excellent time-frequency complex spectrum of the input seismic trace.

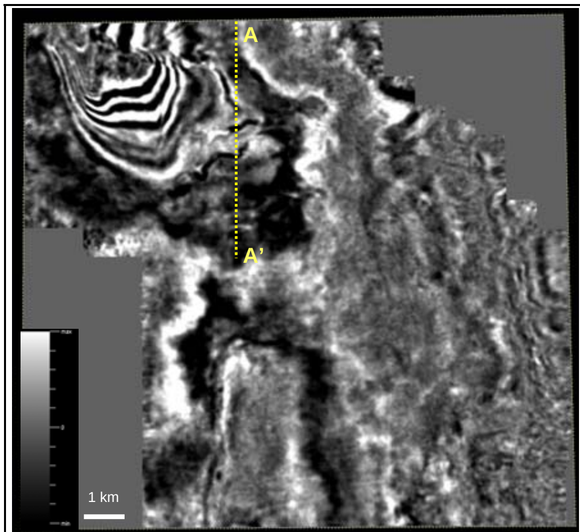

Figure 2: Time slice at t=1.05s through an amplitude volume acquired over west Texas. Line AA' is displayed in Figure 6. Data courtesy of Burlington Resources.

Given the complex spectra at every time sample, we compute the skewness, peak frequency, peak amplitude, peak amplitude above average, and peak phase, and discard the spectral components, since they require too much disk space. Figure 3 and 4 show the peak frequency and quartile skewness respectively. It is easy to see that peak frequency is very noisy and some geologic features are smeared, while skewness gives a much better result in detecting channels (B, C, and D in Figure 4) and erosional unconformity (E in Figure 4). Not surprisingly, since quartile skewness is obtained from 4 spectral components, it is less sensitive to noise than the peak frequency, which is a measure of a single spectral component.

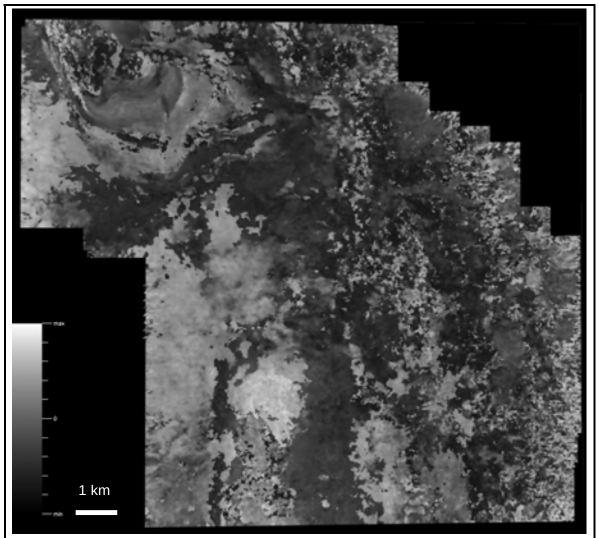

Figure 3: peak frequency calculated from seismic data shown in Figure 2.

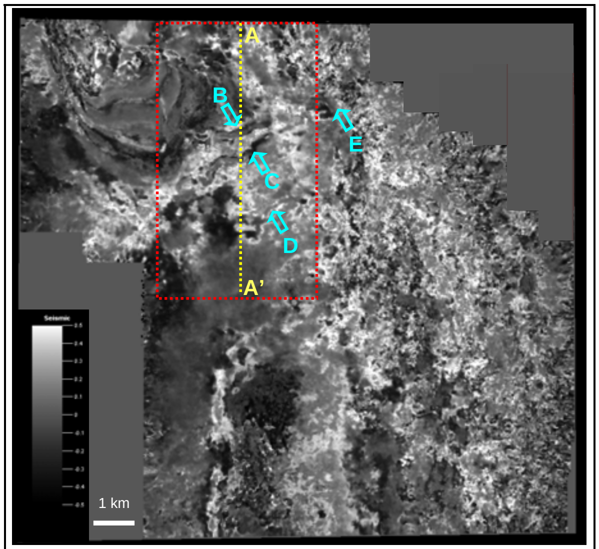

Figure 4: Quartile skewness corresponding to figure 2. It clearly show the channels and other geologic features.

Figure 5 shows the zoomed-in result of the red rectangle zone of Figure 4 and the skewness curve extracted along seismic line AA’ and we plot it as the yellow curve on the right side. We also plot representative spectra from five locations along the line. Note that channels cut through by AA’ correspond to relatively low skewness values indicated by green lines. The two branches of channel D correspond to bimodal spectra and give rise to a lower skewness than other locations.

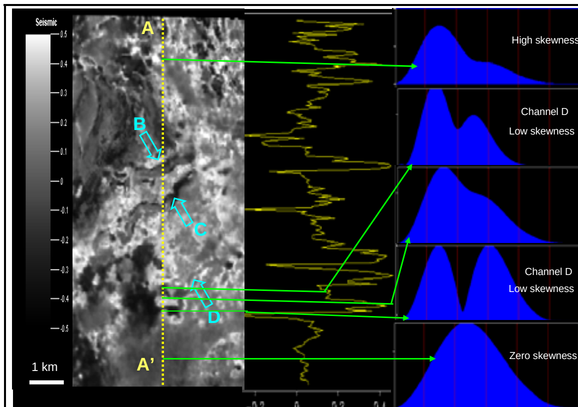

Figure 5: Demonstration of skewness and spectra. Note that channels correspond to low skewness resulting from the bimodal characteristic of the spectrum.

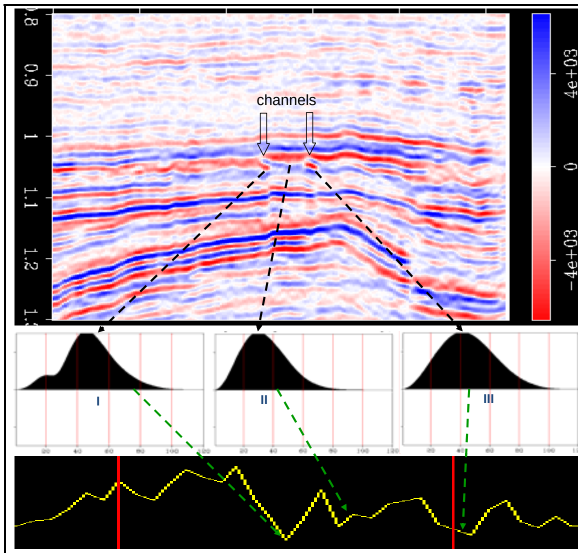

Figure 6: Vertical slice through the seismic amplitude volume along AA’, three frequency spectra and the skewness curve corresponding to t=1.05 s. Thin channels indicated by the block arrows give rise to thin-bed tuning, a correspondingly high dominant frequency which in turn produces low skewness.

Figure 6 shows vertical slice through the original seismic amplitude data along line AA’. We also display three representative spectra and the skewness curve. We note that the two channels seen on the vertical seismic section are represented by low skewness values which result from the fact that the dominant energy of spectra (I and III) corresponding to the two channels shifts towards the higher frequency compared with spectra II. These two channels can also be easily seen on the peak frequency.

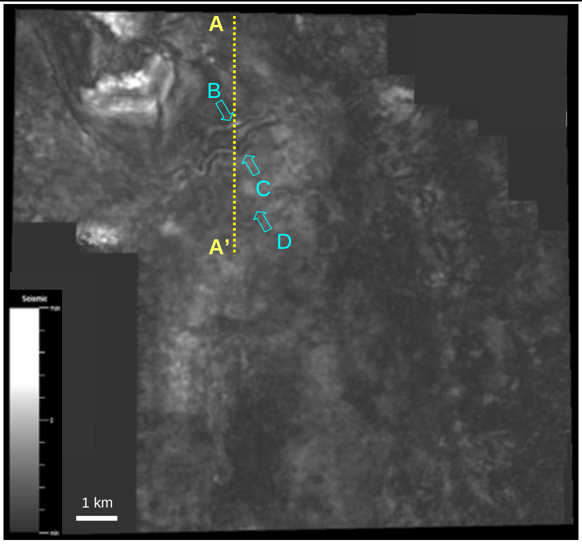

Figure 7: Time slice at t=1.06s through the peak spectral amplitude corresponding to the conventional amplitude time slice shown in Figure 1.

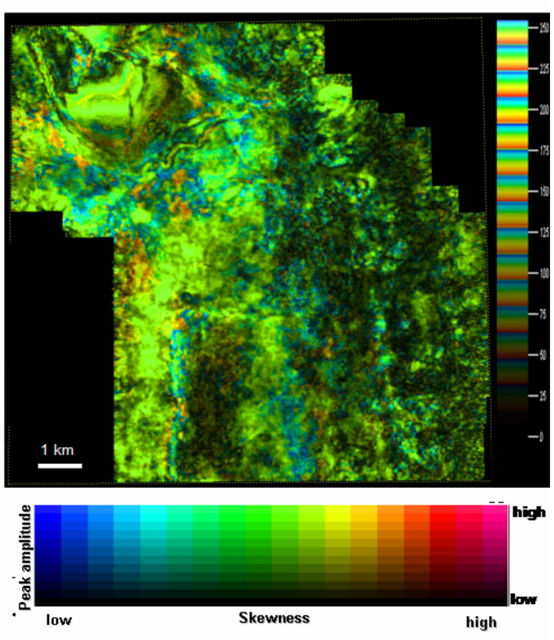

Figure 8: Composite display of skewness (Figure 4) with peak amplitude (Figure 7).

Figure 7 is a time slice at t=1.05 s through the peak amplitude volume clearly delineates channel C. In contrast, channel B and D is much better delineated by the skewness time slice shown in Figure 4. In Figure 8 we combine both skewness and peak magnitude using a 2D color bar, with skewness modulating the hue, and peak magnitude modulating the lightness. Channels and several other subtle geologic details are well illuminated.

One thing we need consider is that whether the measure of skewness is valid for spectrally balanced data, other in the processing shop, or through spectral decomposition. Figure 9 shows the comparison of the skewness curves along AA' at time t=1.05s. The two curves demonstrate very good correlation, and most of skewness lows obtained from non-spectrally balanced data can still be found in the skewness curve calculated from the spectrally balanced data.

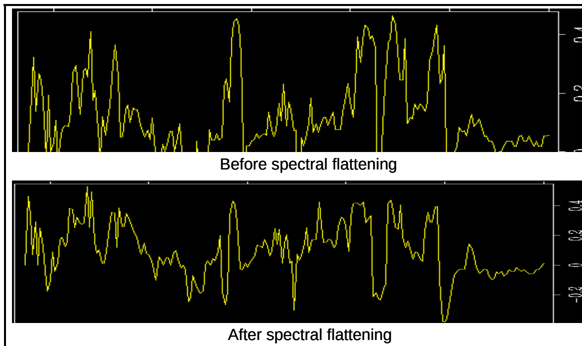

Figure 9: Comparison of skewness along AA' at time *t*=1.05s. calculated (a) before, and (b) after spectral balancing.

Conclusions

Spectral skewness computed from volumetric spectral components can be used to accurately map frequency shifts due to channels, upward-fining, and upward coarsening. We find skewness to be a robust spectral measure that compliments the information content of the peak amplitude and peak frequency.

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