SPECTRAL DECOMPOSITION MADE SIMPLE

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ABSTRACT

Spectral decomposition enables the resolution of seismic data to be improved significantly yielding a new possibility to map thin layers such channel sands and any other stratigraphic features. It has also been used in reservoir characterization. There are three methods for implementing spectral decomposition i.e., The Short Time Fourier Transform, the Continuous Wavelet Transform and the Matching Pursuit Decomposition. Among three of them, the Matching Pursuit Decomposition seems to be the most sophisticated one. It gives the best resolution among them. A simple and logical approach for explaining the spectral decomposition methods together with real data examples are presented in this paper by avoiding complex mathematical formulation.

Key word: channel sand reservoir, resolution, spectral analysis, stratigraphic traps, tuning thickness

I. INTRODUCTION

Spectral decomposition has been frequently used in the processing of seismic data, such as digital filtering, spectral analysis and signal analysis. However, only recently that spectral decomposition has been used for the interpretation of seismic data (Johann and Ragangin, 2003; Patyka et al., 1988, 1999; Bahorich et al., 2001). By definition the spectral decomposition itself refers to any method which produces a continuous time-frequency analysis from a single seismic trace (see Figure 1).

Spectral decomposition can be used to display broad band seismic data into its frequency components. Analysis of frequency spectra and individual frequency component can provide additional information than obtained from other conventional analysis of broad band data.

Nowadays, spectral decomposition is becoming one of the central attentions which is expected to resolve thin layer problems encountered in oil and exploration.

Partyka (2001) and Kishore et al. (2006) have used spectral decomposition for thickness estimation of thin subsurface layers, Partyka et al.,(1999) have also used it in reservoir characterization. Harilal et.al., (2009) has been successfully used spectral decom-

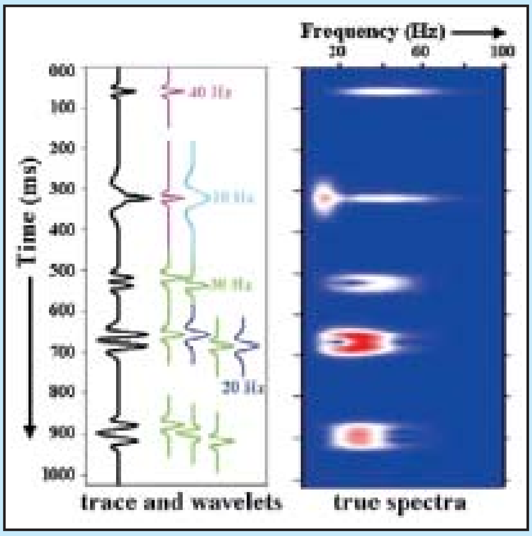

Figure 1
The basic principle of spectral decomposition of a seismic trace containing four different frequencies (Castagna and Siegfried, 2003)

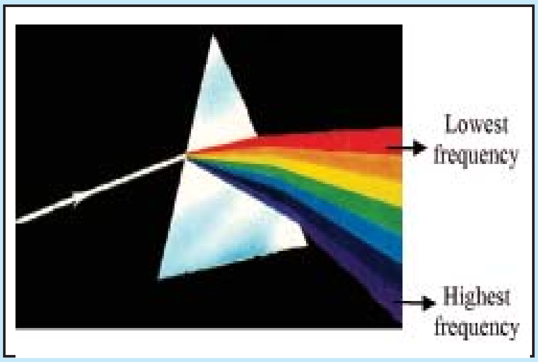

Figure 2
The principle of spectral decomposition in optic where a white light can be decomposed into seven colors

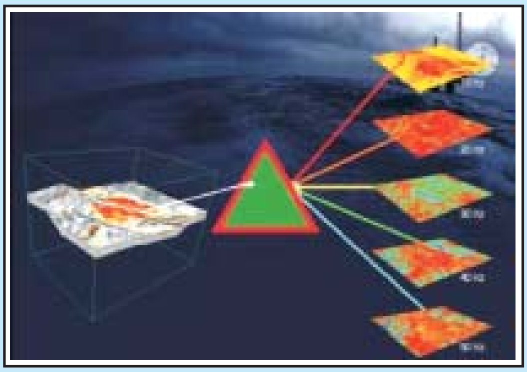

Figure 4
A schematic diagram demonstrating the decomposition a subsurface strata into five tuning frequencies (Schlumberger article)

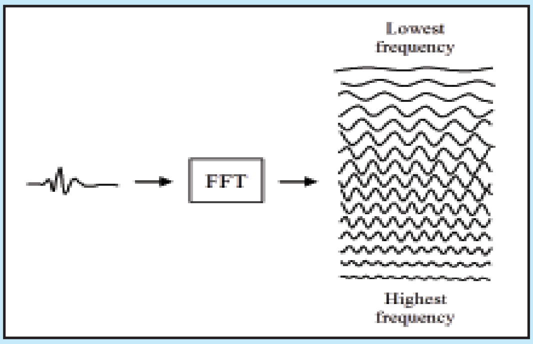

Figure 3
The principle of decomposition of seismic wavelet into its frequency components using the Fast Fourier Transform

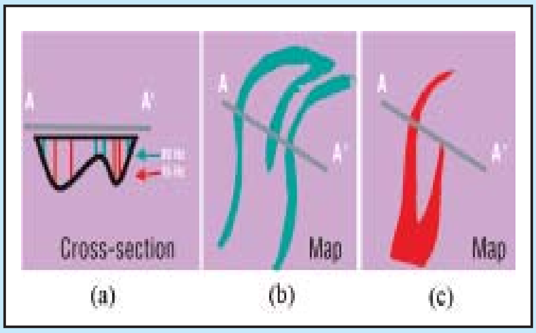

Figure 5
A schematic diagram demonstrating the effect of tuning frequency in subsurface mapping (Laughlin et al, 2003)

position to map thin sandstone reservoir in the C-37 prospect in the Tapti-Daman subbasin of Mumbai basin, offshore of western India.

II. BASIC PRINCIPLE

A. *The Spectral Components*

Seismic volumes are complex images of reflections, wave interferences, tuning effects, attenuation, absorption etc. It can be difficult to know what to expect a given layer or stratigraphy to look like in the seismic, or what a particular seismic reflection pattern represents (Hall and Trouillot, 2004). By using spectral decomposition method, the broad band seismic data can be decomposed into its frequency component. Spectral analysis of individual frequency component can provide additional information than obtained from other conventional analysis of broad band data.

The philosophy of spectral decomposition originates from optics. Newton (1642-1727) has proved that the white light is composed of seven different colors each having its own frequency. In other words, these frequencies are the components which construct the spectrum of the white light. (Figure 2)

In seismic exploration, according to Fourier synthesis (1822) a seismic wavelet is also composed of many different waves, each having specific frequency (Figure 3).

This principle can be expanded to analyze wave interference commonly found in seismic exploration

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which is usually referred to as the tuning effect (Figure 4).

From this figure it can be concluded that a thick layer has a wide frequency spectrum, without high frequency ripple, while a thin layer has a frequency spectrum which contains high frequency ripple. To demonstrate the application of this principle, let us investigate the following geologic model (Figure 5a).

Suppose we want to map thin layer whose thickness is represented by the green color. According to spectral decomposition principles if the thin layer appears at a tuned frequency of 30 Hz, a thick layer whose thickness is represented by red color will appear with a tuning frequency lower than the first one; i.e., 15 Hz. The analogy of the principle mentioned above can be demonstrated by the following Figure 5b and 5c. It can be concluded that different tuning frequency reveals different structure. In this case green prism represents spectral decomposition process.

Figure 6 demonstrates another interesting feature related to spectral decomposition. In this case the wedge model is used. It can be seen that the temporal thickness in the time domain (upper figure) is greatly exaggerated in the frequency domain (lower figure). If for example we have top and bottom of a layer is separated by a temporal thickness of 10 msec, it means that in the frequency domain, they will be separated by 1/10 msec = 100 cps. If we take a smaller temporal thickness say 4 msec, then the separation in the frequency domain will be 1/4 msec = 250 cps. This means the smaller the separation in the time domain, the larger the separation in the frequency domain and vice versa. The relationship is represented by the curve line shown in the lower (Figure 6).

B. *The Tuning Thickness*

At a thickness less than a quarter wavelength, amplitudes of the seismic wavelet superimposed yielding resultant amplitude which depends on the thickness of the thin bed represented as notches (Figure 7). The peak frequency corresponds to the frequency

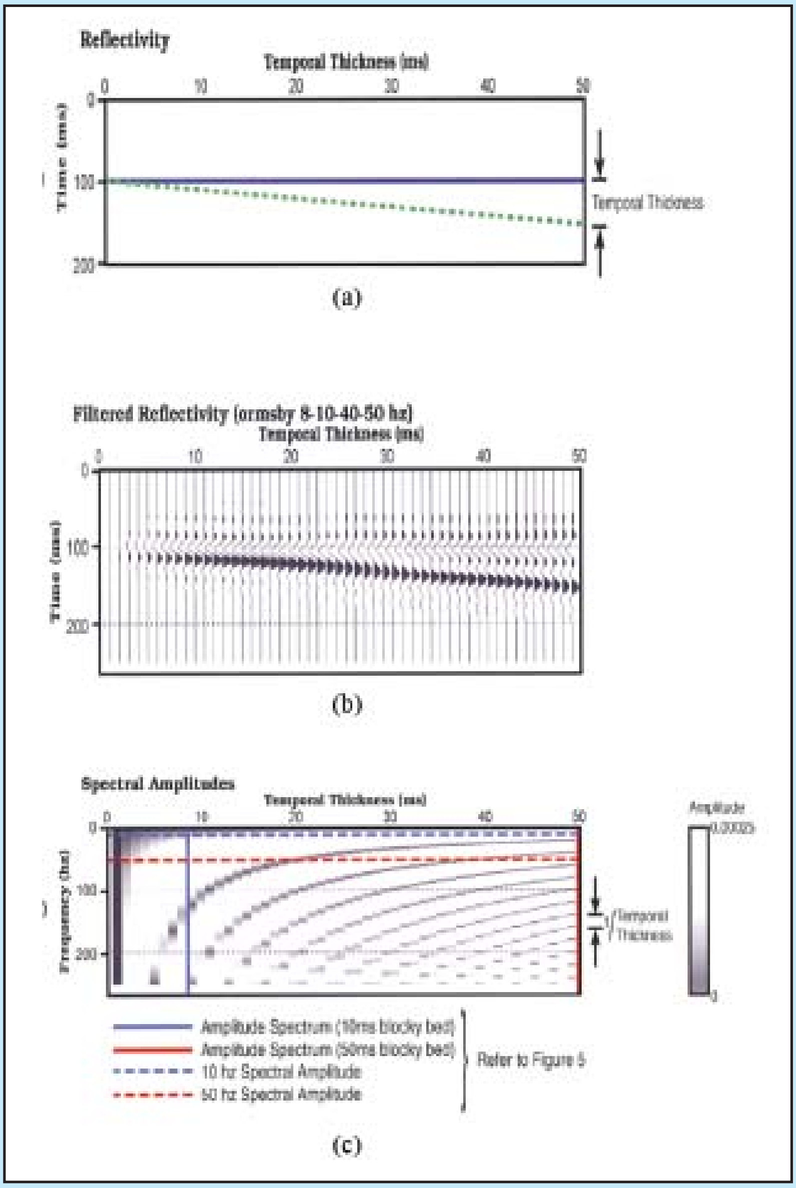

Figure 6
(a). A wedge model representing a strata with thickness variation. It thickening to the right or thinning to the left. (b). The corresponding synthetic seismic section of figure 3a. (c). The spectral amplitude as a function of temporal thickness and frequency (Partyka, 1999)

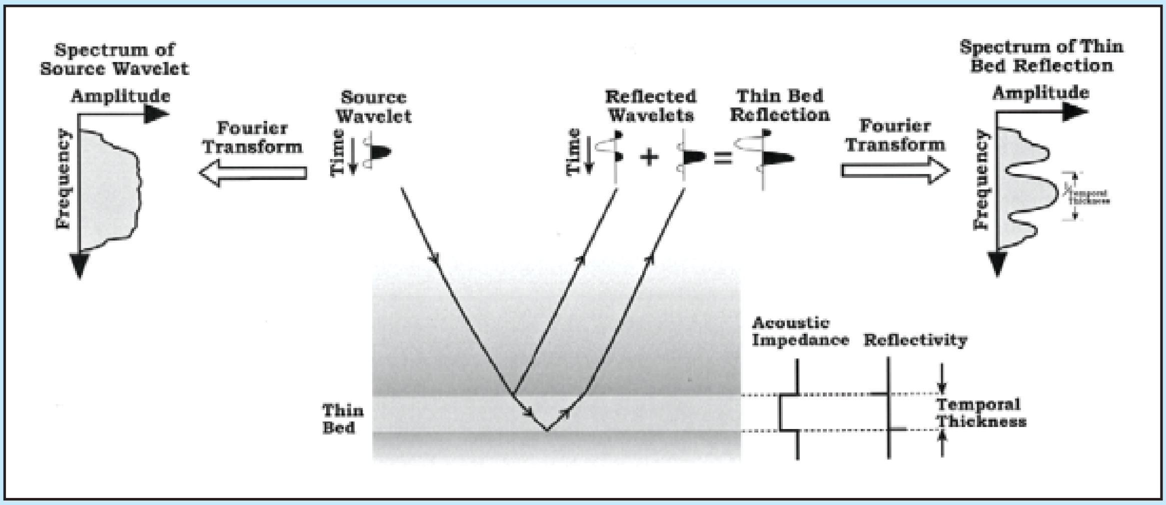

Figure 7
A thin bed model demonstrating the effect of the thickness in the amplitude spectrum (Partyka, 1999)

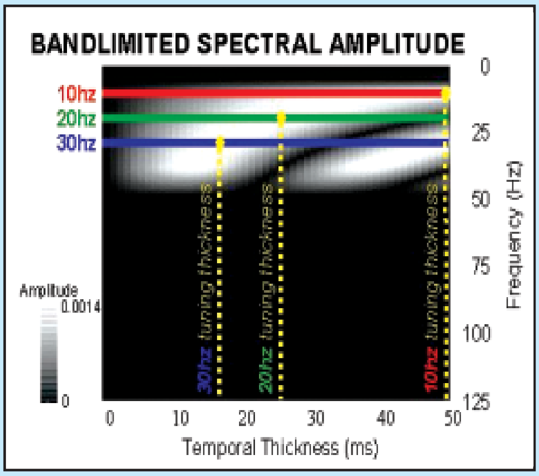

Figure 8
A band limited spectral amplitude as a function of temporal thickness and frequency (BP article)

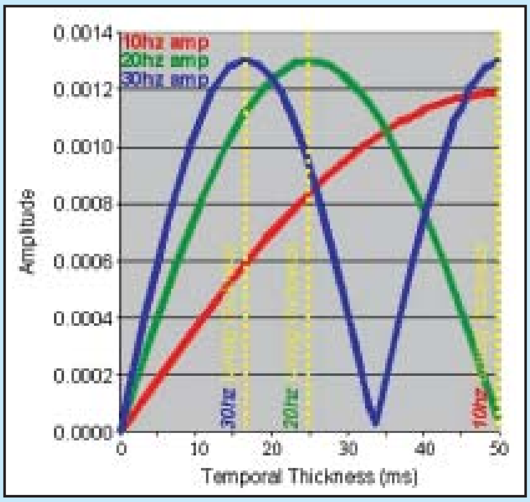

Figure 9
The tuning frequency as a function temporal thickness (BP article)

value at which the maximum amplitude occurs, and this maximum amplitude is the peak amplitude.

Figure 8a demonstrates the peak amplitude associated with the dominant frequency of the wavelet. The blue one with a frequency of 30 Hz has the smallest tuning thickness, i.e. 17 msec. The green one with a frequency of 20 Hz has the moderate tuning thickness which is 25 msec. And the red one with a frequency of 10 Hz has the thickest tuning thickness of around 50 msec. Incorporation of this fact into Figure 8 yields an enlarged picture as given in Figure 9 (see below) which analogically can be exaggerated as given in Figure 10.

An important rule of thumb which can be applied from the spectral decomposition is that the period of the notches in the amplitude spectra depends of the thin bed thickness.

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C. SPECTRAL DECOMPOSITION METHODS

There are a variety of spectral decomposition methods, the most commonly used can be grouped in three categories (Rojas, 2008), i.e.: Short Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), and Matching Pursuit Decomposition (MPD). None of this methods are right or wrong;

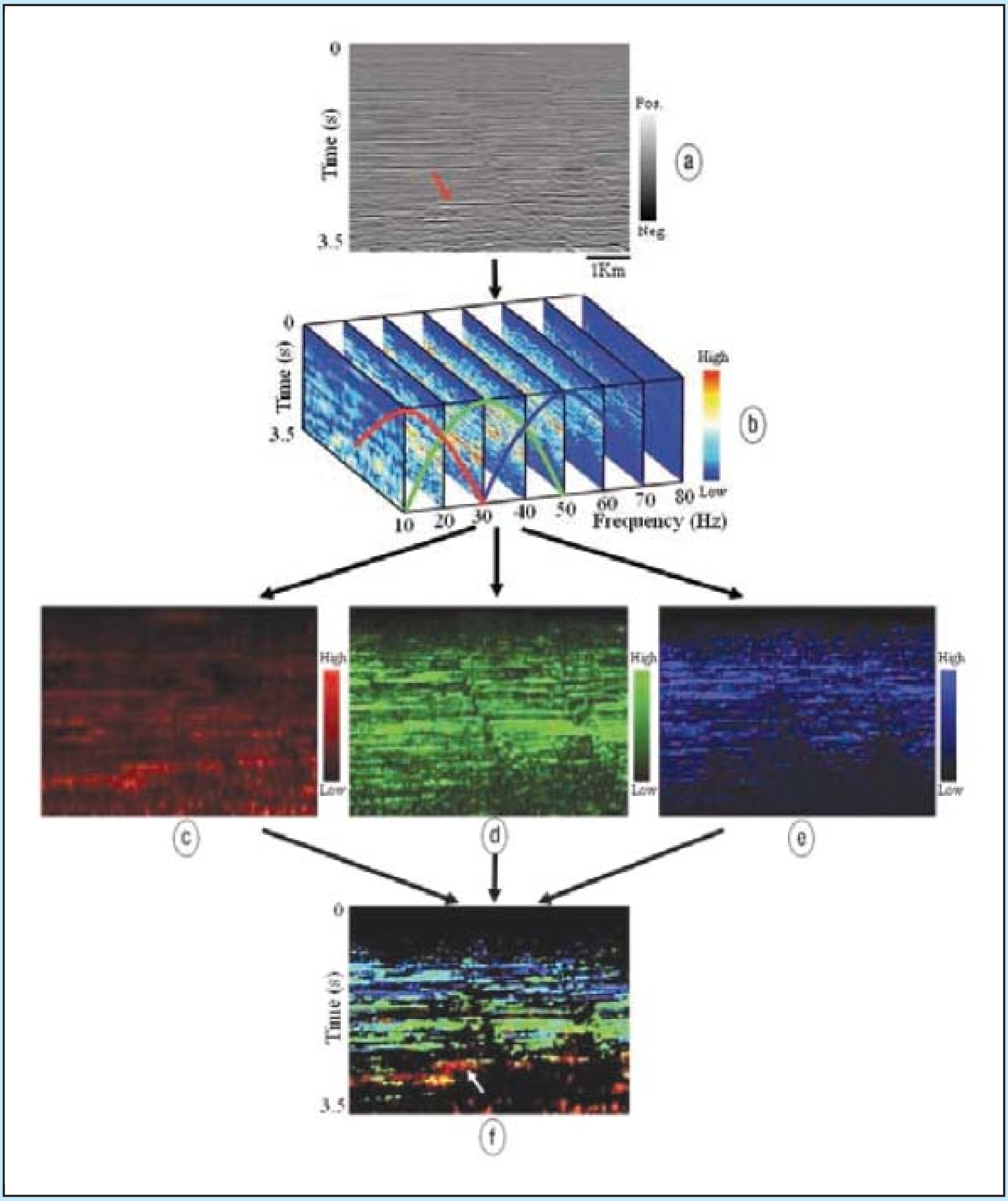

Figure 10
A simplified spectral decomposition application (Liu, 2007)

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each method has its own advantages and disadvantages, and different application requires different methods (Castagna and Sun, 2006).

1. The Short Time Fourier Transform (STFT)

In the STFT, a time frequency spectrum is produced by taking the Fourier transform over a chosen time window. When a seismic signal is transformed into the frequency domain using the Fourier transform, it gives the overall frequency behavior. This transformation is inadequate for analyzing a non-stationary signal (Sinha et al., 2005). In this method, the seismogram is segmented by multiplication with a window function. The Fourier transform of this windowed seismogram is then computed and the process is repeated by shifting the window in time.

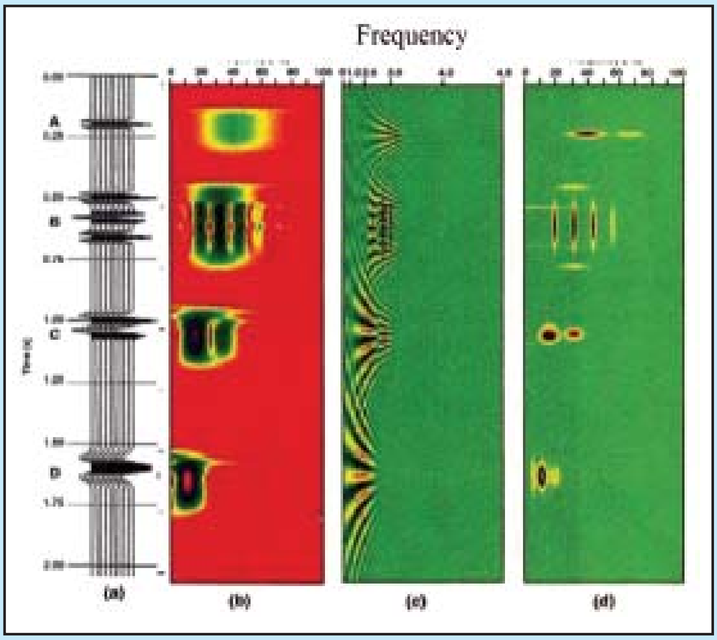

Figure 11
Comparison of spectra obtained from Short Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), and Matching Pursuit Decomposition (MPD)

2. The Continuous Wavelet Transform (CWT)

In the CWT the wavelet is scaled in such a way that the time support changes for different frequencies. A wavelet is defined as a finite energy function with a zero mean belongs to Hilbert space. By scaling and transforming this wavelet, we produce a family of wavelets which are function of scale parameter and translation parameter. Once a wavelet family is chosen, then a Continuous Wavelet Transform at a scale and translation time can be defined.

3. The Matching Pursuit Decompositiion (MPD)

The Continuous Wavelet Transform (CWT) mentioned above has a better time-frequency resolution than the STFT. The resolution of the STFT is not uniform across the entire time-frequency plane. The CWT has good time resolution for high frequencies therefore poor frequencies resolution. It has also good frequency resolution for low frequencies. So, the CWT alone is not sufficient to get good frequency resolution at intermediate to high frequencies an interval where seismic data are rich in frequencies. In this case the Matching Pursuit Decomposition (MPD) provides better resolution (Mallat and Zhang, 1993).

Similar to the CWT, in MPD a set of basis function are generated by scaling, translating, and modulating a single window function as :

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

Where $w(t)$ is a Gaussian window, u is the time delay (translation), σ is the spread in the time axis (scale), *wð* is the center (angular) frequency modulation, and ϕ is the phase shift. Thus, a Gabor wavelet is characterized by a set of four parameters, $\gamma = \{u, \sigma, \omega, \phi\}$.

To understand the inferiority and superiority between STFT, CWT, and MPD, let us investigate the following figure (Chakraborty and Okaya, 1995)

Figure 11(a), is the synthetic seismogram containing wavelets with different frequency and different times indicated by (a),(b),(c), and (d). It can be seen at a time position less than 0.25 sec, by using STFT wavelet. A can be decomposed into a frequency around 40 Hz. At an interval from 0.50 to 0.75 sec, a group of wavelet B, by STFT can be decomposed into three different dominant frequencies. At a time around 1.0 sec an overlapping wavelet C, by STFT can be decomposed into two different dominant frequencies which is lower than wavelet B. Finally, the low frequency wavelet D at a time interval between 1.5 – 1.75 sec, by STFT is represented by a low frequency spectrum with a dominant frequency of 12 Hz.

The above figure has demonstrated the ability of spectral decomposition method in resolving interesting feature in seismic time section. By contrast to figure 11(b), figure 11(d) display the superiority of the MPD compared to STFT. It can be seen clearly that frequency resolution of MPD is much higher than the STFT. But not only does the MPD has a higher resolution than the STFT, the MPD has also a better time resolution than the STFT.

Figure 11(c) is the CWT of figure 11(a), it can also be seen that the CWT has successfully decomposed seismogram into scale index and time position indicated by the center of the ripples pattern. The scale is inversely proportional to the frequency, since the smaller scale, the higher the frequency and vice versa.

III. IMPLEMENTATION OF SPECTRAL DECOMPOSITION

The spectral decomposition can be applied to the 2D seismic data as well as the 3D seismic data. For application in the 3D seismic data, the following workflow can be done.

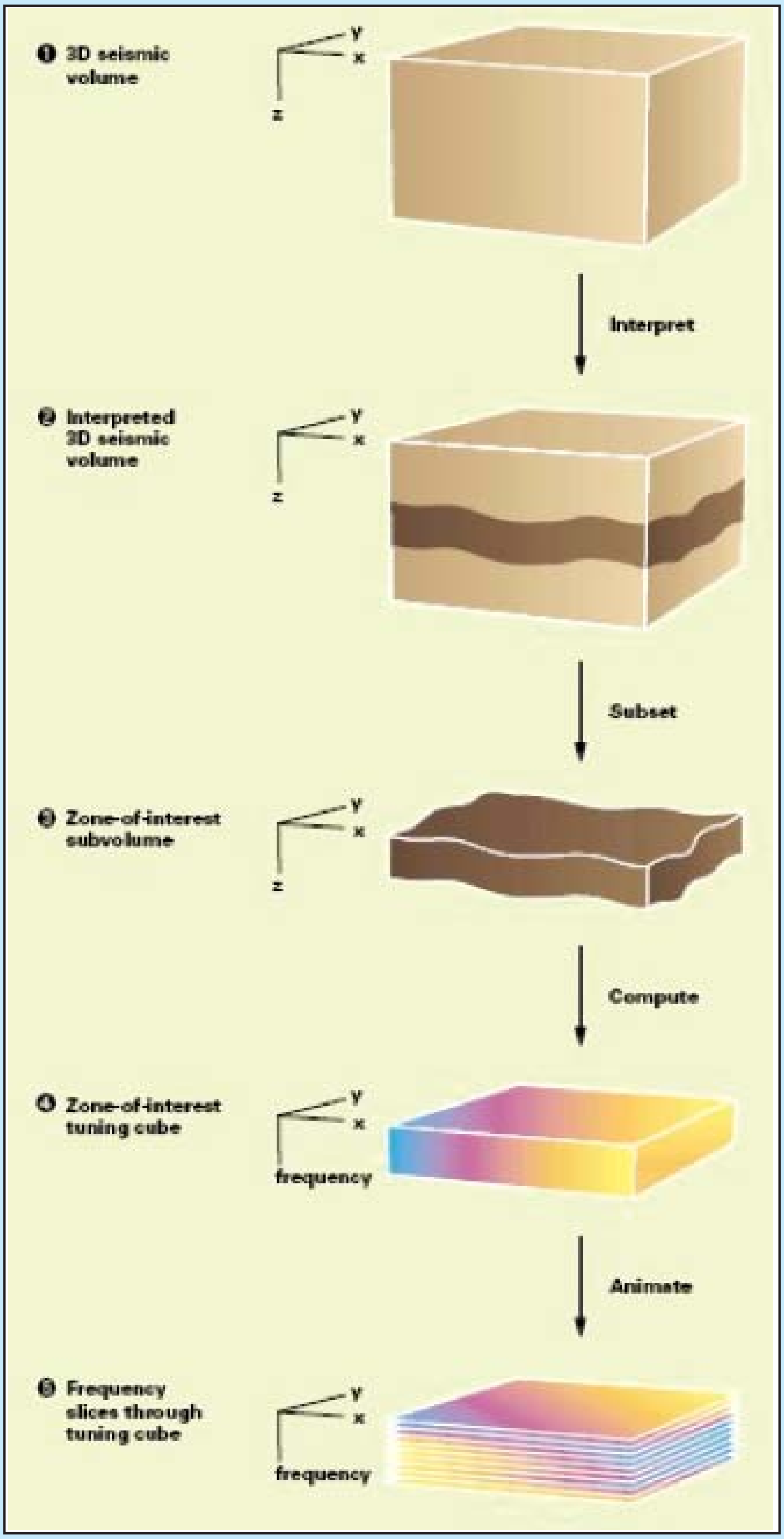

Figure 12
The schematic diagram of the workflow for implementing spectral decomposition

IV. RESULT AND DISCUSSION

The purpose of this chapter is to explain the success stories of spectral decomposition in solving problems encountered in oil and gas exploration. Examples are selected from the published literatures as cited.

A. *The 2D seismic data examples*

B. *The 3D seismic data examples*

IV. CONCLUSION

1. Spectral decomposition offers a new possibility for exploring thin layer
2. In general the thinner the layer, the higher the tuning frequency and vice versa
3. A subsurface geological feature has a specific tun-

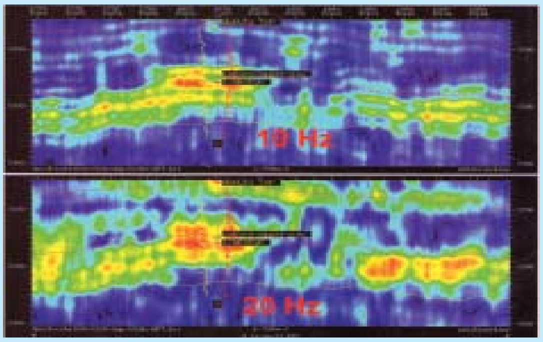

Figure 13
Spectral decomposition applied to 2D seismic data tuned at frequency 10 Hz and 20 Hz. At a tuned frequency of 10 Hz a reef built up like structure appears more clearly than at a tuned frequency of 20 Hz (Johann, et.al, 2003)

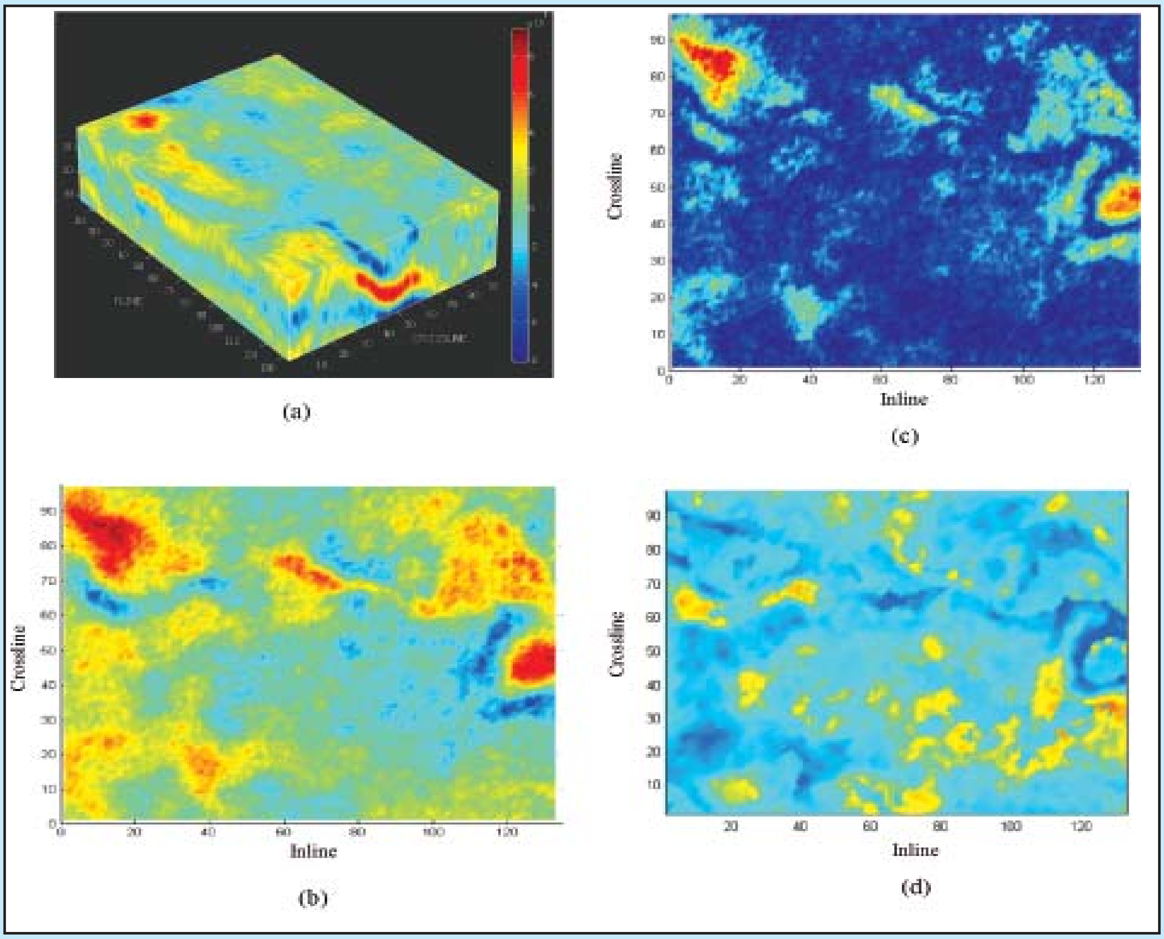

Figure 14
Spectral decomposition applied to 3D seismic data (X-Gas field, Mexico Gulf). (a) 3D seismic C-Formation. (b). Amplitude time slice at 92 msec. (c) CWT analysis tuned at 83 Hz. (d) MPD analysis tuned at 89 Hz. Observe the superiority of (c) and (d) compared to (b)

ing frequency to make it appear in the seismic section as well as in the time slice map

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