

High-dimensional resolution enhancement in the continuous wavelet transform domain

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Summary

We present a method to enhance the bandwidth of seismic data in the continuous wavelet transform (CWT) domain. By utilizing the features of CWT in detecting time-variant frequency content and automatically designing band-dependent time windows, we can enhance the seismic bandwidth mostly based on signal. A high-dimensional implementation of the method enables us to make full use of the information from nearby data to stabilize the algorithm. A real data example shows that applying the proposed method at different processing stages has different benefits. If implemented properly, the approach is AVO friendly and compares well with conventional spectrum balancing.

Introduction

Seismic imaging with high temporal and spatial resolution is important for detailed structural and stratigraphic interpretation of the subsurface geology (Pierce et al. 2010; Yu et al. 2012). The factors affecting spatial resolution are discussed by Vermeer (1999). The temporal resolution for land seismic data is conventionally enhanced by surface-consistent spiking deconvolution, which attempts to remove the temporal wavelet and recover the reflectivity of the subsurface. Due to non-stationary properties of the seismic wavelet, noise and the assumptions of the earth convolution model, the temporal resolution improvement obtained from deconvolution may not be enough. As such, further enhancement of temporal resolution may be performed. One of the methods used in the industry is spectral balancing (Nagarajappa and Downton, 2009). The conventional implementation of spectral balancing does not optimize the resolution of time and frequency and is unable to enhance the bandwidth based on signal.

Wavelet transform (WT) has been applied in seismic data processing for more than a decade (Miao and Moon, 1994). The distinct advantage of the WT over the conventional Fourier Transform (FT) is that the WT has the capability of combining the features of both time and frequency information. The WT also distinguishes itself from Short Time FT (STFT) in terms of window width. The width of the STFT window is fixed while the WT uses a variable window dependent of frequency band. The continuous WT (CWT) has been used in noise attenuation (Miao and Cheadle, 1998) and spectral decomposition (Miao et al., 2007). Smith et al. (2008) used the harmonics and sub-harmonics predicted and computed with the CWT to extend the bandwidth.

In this paper, we propose a method, which we refer to as high-dimensional resolution enhancement (HDRE), to enhance the bandwidth by utilizing high-dimensional data in the CWT domain.

Method

The CWT has been explained by Miao and Moon (1994), Qian (2002) and Smith, et al. (2008). It is the convolution of a signal f(t) with a scaled (s) and translated (τ) wavelet Ψ (Qian, 2002).

$$F_{W}(s,\tau) = \frac{1}{\sqrt{|s|}} \int \Psi^*\left(\frac{t-\tau}{s}\right) f(t) dt$$

Where Ψ^* is the complex conjugate of Ψ . Each scaled (s) wavelet Ψ has different frequency band.

The construction of the signal f(t) from the CWT involves a double integral of the scaled (s) and translated (τ) function $F_w(s, \tau)$.

$$f(t) = \frac{1}{C_{\Psi}} \iint \frac{1}{s^2} F_W(s,\tau) \Psi\left(\frac{t-\tau}{s}\right) ds d\tau$$

Where C_{Ψ} is the admissible constant given by admissibility condition of the wavelet Ψ .

As shown in the flowchart (Figure 1), the key step is to balance the existing frequency bands and predict the attenuated bands from existing signal bands. The multi-dimensional data D(x, y, o, t) in inline (x), crossline (y), offset (o) and time (t) are first transformed into CWT domain with amplitude

 $A(x, y, o, \tau, f)$ and phase $P(x, y, o, \tau, f)$. By analyzing the signal to noise ratio from multi-dimensional data for each frequency band in CWT domain, we balance the amplitude in the CWT domain and predict the amplitude

 $A'(x_1, y_1, o_1, \tau, f)$ and phase $P'(x_1, y_1, o_1, \tau, f)$ of the attenuated bands from existing signal bands for the central trace with inline x_1 , crossline y_1 and offset o_1 . Finally the central trace $D'(x_1, y_1, o_1, t)$ with enhanced bandwidth is reconstructed by inverse CWT.





Field data example

We tested the high-dimensional resolution enhancement (HDRE) algorithm with a land dataset from Western Canada. The major target is above 900 ms (Figure 3a). As indicated in blue arrows in Figure 3a, a wedge structure is at around 650 ms on the left side of the section. Robust surface-consistent spiking deconvolution provided a relatively broad bandwidth from 10 to 90 Hz (red curve of Figure 3d).

The HDRE was first applied to pre-migration data to enhance the temporal resolution before forming the common offset gathers for velocity analysis. The dataset is quite noisy with both random and coherent noise, so the neighboring 5 inlines, 5 crosslines and 9 offsets traces were analyzed to enhance the bandwidth. As shown in the gathers of Figure 2, there are strong surface-related and inter-bed multiples. If we compare the semblances before (Figure 2a) and after (Figure 2b) HDRE, we can observe that multiples, particularly the inter-bed multiples, and primaries are more distinguishable after applying HDRE. This helps to improve the accuracy of velocity picking.



Figure 2: Velocity semblances (left panels) and common offset gathers (right panels) before (a) and after (b) high-dimensional resolution enhancement (HDRE).

To compare with conventional spectrum balancing, HDRE was then applied to poststack data. As indicated in blue arrows in Figure 3a and Figure 3b, the tuning effect of the wedge structure due to limited bandwidth is significantly reduced and the wedge structure is better defined after HDRE. Comparing the conventional spectral balancing and HDRE, we can observe that although spectrum balancing (green curve in Figure 3d) does balance the spectrum from 10 to 95 Hz, it does not preserve the spectrum details very well as shown in orange arrow in Figure 3d. These spectrum details reflect the geological variation of the subsurface. From the stack section in Figure 3c, we can see that the definition of the wedge structure is not as clear as that after HDRE.



Figure 3: Comparison of HDRE (b) and conventional spectral balance (c) on post-stack data (a) and their spectra (d).

The most common processing stage to apply HDRE is on pre-stack time migration (PSTM) gathers as shown in Figure 4, in which six offset-ordered CDP gathers are compared before and after HDRE. The RMS amplitudes for the selected time window are also displayed on the top sections of the gathers. The result shows that HDRE can preserve the amplitude variation with offset (AVO) well. The spectrum details after HDRE (blue curve in Figure 4c) follow those of the original data. The PSTM stacks are shown in Figure 5a and Figure 5b for before and after HDRE respectively. We also observe a significant enhancement of bandwidth in the migrated stacks after applying the algorithm. It's clear that with HDRE, the event between 850 to 900 ms is much better resolved. More structural details are revealed for easier interpretation as shown with purple arrows.



Figure 4: PSTM CDP gathers before (a) and after (b) HDRE, and their spectra (c).



Figure 5: PSTM stacks before (a) and after (b) HDRE, and their spectra (c).

Conclusions

The CWT domain is a desirable domain for temporal resolution enhancement because it optimizes the time and frequency resolutions. Therefore the dyadic increase of frequency panels enables the possibility of multi-resolution analysis. By analyzing high-dimensional data in the CWT domain, we can robustly enhance the low and high frequency content mostly based on predicted/estimated signals.

Field data examples show that applying HDRE at different processing stages has different benefits. With appropriate implementation, HDRE is AVO friendly and a better alternative to conventional spectrum balancing. The effect of enhanced bandwidth by applying HDRE in prior can be clearly observed after pre-stack time migration, which sharpens the image, reduces the ringing and better defines detailed structures.

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