Comparison of frequency attributes from CWT and MPD spectral decompositions of a complex turbidite channel model

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Summary

Various studies have demonstrated the usefulness of spectral decomposition and its associated frequency attributes in seismic interpretation and hydrocarbon exploration. However, many different techniques for spectral decomposition exist in the petroleum industry, creating a need for comparative studies of these techniques to evaluate their utility. In this work, we compare the results of the application of the CWT and MPD algorithms and associated frequency attributes to a complex turbidite model. Our results indicate that better resolution of stratigraphic features is achieved by the MPD algorithm. These improvements include sharper definition of lateral stratigraphic changes and detection of subtle channel features associated with off-peak frequencies. We also show the effective extraction of stratigraphic features associated with off-peak frequencies achieved by principal component analysis. We believe a quantitative assessment of the relationship between the rock properties volume and frequency attributes will provide useful insight during future work.

Introduction

Spectral decomposition is a seismic analysis technique that decomposes seismic data into the time-frequency domain, which often contains useful information for layer thickness estimation (Partyka et al.,1999; Puryear and Castagna, 2008), stratigraphic interpretation (Marfurt and Kirlin, 2001; Puryear and Castagna, 2008), and hydrocarbon indication (Castagna et al., 2003; Sinha et al., 2005). There are many spectral decomposition algorithms and frequency attributes that can be generated from spectral decomposition volumes. In this paper, we compare results obtained from two common spectral decomposition algorithms – the Continuous Wavelet Transform (CWT) and Matching Pursuit Decomposition (MPD). Because of the large volume of data produced by the spectral decomposition process, the general objective of frequency attributes applied to spectral decomposition is to reduce the quantity of cumbersome frequency volumes to a manageable number while retaining the most geologically pertinent information contained within the redundant frequency volumes. Common frequency attributes include peak frequency/peak amplitude mapping (Marfurt and Kirlin, 2001) and principal component analysis of spectral components (Guo et al., 2006). Our objective is to compare both the spectral decomposition results generated by the CWT and MPD and the frequency attributes derived from those results. We apply the algorithms to synthetic data generated by the application of the 3D "Huygens" method to a complex turbidite rock properties model (van Hoek and Salomon, 2006).

Theory and Method

The CWT is a commonly-used wavelet transform that utilizes orthogonal basis wavelets in order to decompose the seismic trace into individual frequency components. The CWT is essentially equivalent to a narrow-band filtering of the data in the temporal domain. We apply CWT to seismic traces using a Morlet wavelet basis function, which utilizes a window that varies as a function of frequency. MPD is a technique for time-frequency analysis that utilizes non-orthogonal basis functions, thereby allowing for atoms with more time compactness and more flexibility in the selection of atoms that match the shape of the trace. We compare the results from the spectral decompositions directly and then use these results as input into peak frequency/peak amplitude mapping and principal components mapping for comparison. Peak frequency/peak amplitude mapping tracks the frequency with the highest amplitude and the amplitude at that frequency along a particular horizon. Peak frequency is strongly related to layer thickness below tuning. Peak amplitude is highly correlated to broadband amplitude, and is therefore a less useful frequency attribute (Blumentritt, 2008). Hence, we focus on peak frequency for comparison between the CWT and MPD. We also perform a principal component analysis of the spectral components in order to isolate frequency bands representative of the data for comparison between the CWT and MPD. We compare the data using identical plotting ranges relative to the standard deviation of the data. We note that the single frequency components, the peak frequency, and the principal components all highlight subtle channel features that respond preferentially to narrow frequency ranges.

Examples

Van Hoek and Salomons (2006) generated the synthetic seismic data using Kirchoff demigration, or ray tracing, followed by standard processing and migration. Figure 1

Comparison of CWT and MPD

shows the spectrum of the seismic wavelet, with a peak frequency of approximately 16 Hz. Figure 2a shows a vertical slice through the impedance model volume with prominent channel belts at the depth range of interest circled, Figure 2b shows the synthetic seismic data and analysis horizon used in subsequent figures, and Figure 2c shows the line of section through a broadband amplitude extraction map.

We illustrate the results of the spectral decomposition algorithms and frequency attributes using several examples. In order to better understand the information content of the principal components, we plot the spectral energy distribution of the first 5 principal components of the spectral components. The peak energy of each increasing component number gravitates toward lower frequencies. We speculate that this tendency is related to the fact that there is more variation in wavelength scale relative to a given feature in the low end of the spectrum than in the high end (i.e. a given quantity of frequency change is more significant in the low end of the spectrum than in the high end of the spectrum). Figure 4 shows a comparison of the 2nd principal components, which are correlated to spectral components of approximately 9 Hz, computed from the CWT and MPD spectral components; the plots are scaled to ± 4 standard deviations. The images show similar channel geometries, both highlighting a channel that is not prominent in the broadband amplitude extraction (Figure 2c) or the 1st principal component extractions. However, the 2nd principal component extracted from the MPD result shows sharper delineation of lateral stratigraphic changes, as indicated by block arrows. Figure 5 illustrates the difference between 5 Hz spectral component maps, also scaled to ± 4 standard deviations, obtained from the CWT and MPD,. The low frequency MPD result isolates a channel meander loop that is not highlighted by any of the CWT frequency components, while the 5 Hz CWT component highlights the same channels that are highlighted by both methods at higher frequencies (see Figures 2c and 3). We believe this discrepancy can be attributed to the long cross-correlation window used by the CWT at low frequencies, which fails to isolate temporally-restricted low-frequency energy. Figure 6 compares peak frequency extractions from the CWT and MPD spectral components. The result obtained from the MPD spectral components displays greater continuity and delineation of the low frequency channel highlighted in Figure 5 than that obtained from the CWT spectral components.

Conclusions

We have compared spectral components and frequency attributes from the CWT and MPD spectral decomposition algorithms applied to a synthetic seismic model of a complex turbidite rock properties model volume. Our results indicate that MPD yields higher resolution of stratigraphic detail than does the CWT in two ways. First, lateral stratigraphic changes appear sharper on the MPD sections, indicative of less energy smoothing in the time domain. Second, low frequency features with limited temporal extent are effectively isolated on MPD, yet averaged out by the CWT due to the variable window smoothing effect. We note that principal component sections beyond the 1st principal component effectively isolate stratigraphic features that are difficult to distinguish on broadband amplitude extractions. It is our expectation that in more complex geological scenarios, principal component analysis will separate intermingled stratigraphic features into "classes" based on optimal spectral response. In future work, we intend to quantitatively link the rock properties model to the responses of frequency attributes and investigate the implications of those attributes for understanding depositional systems.

Acknowledgements

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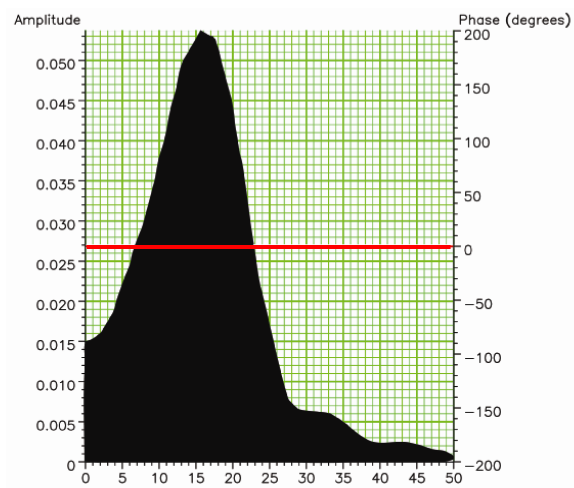

Figure 1. The spectrum of the synthetic seismic wavelet. The peak frequency is about 16 Hz.

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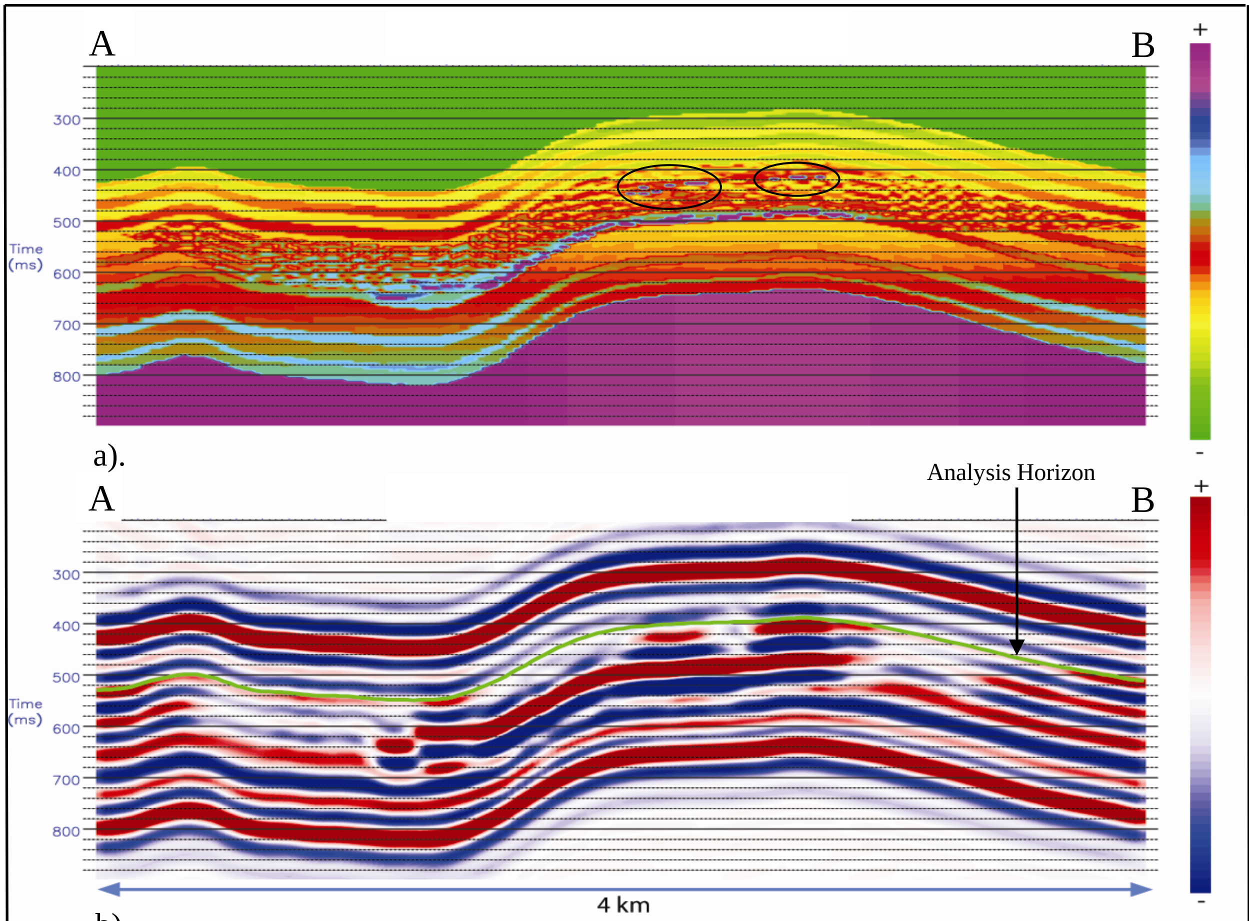

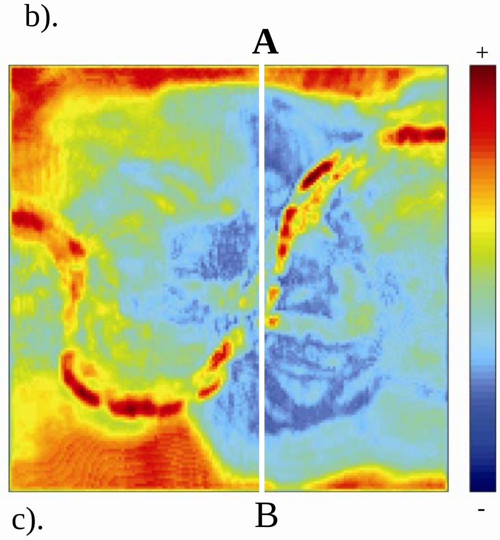

Figure 2. (a) Impedance model with prominent channel belts circled, (b) synthetic seismic model with analysis horizon (green), and (c) cross section line through amplitude extraction.

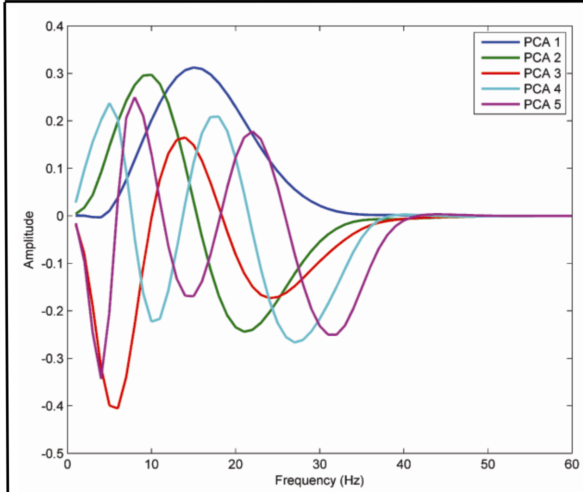

Figure 3. Principal components of spectral components. Peak spectral energy gravitates toward lower frequencies with increasing component number.

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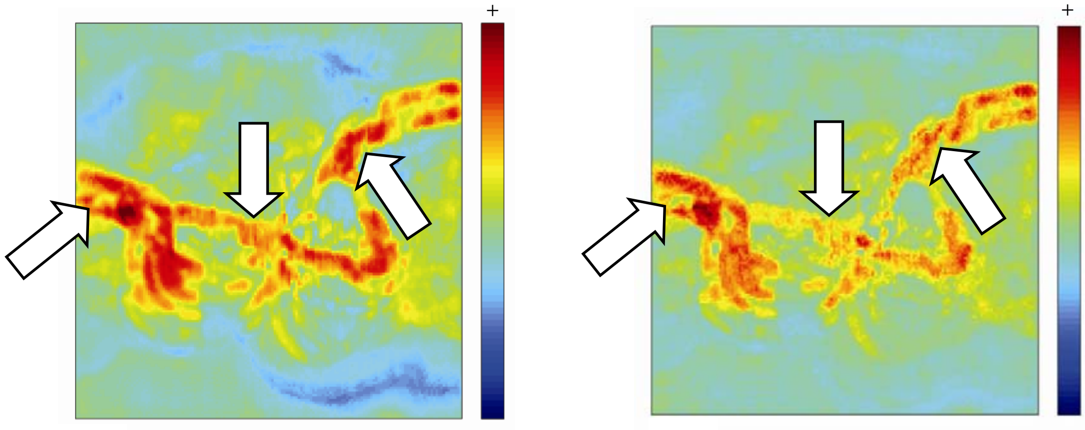
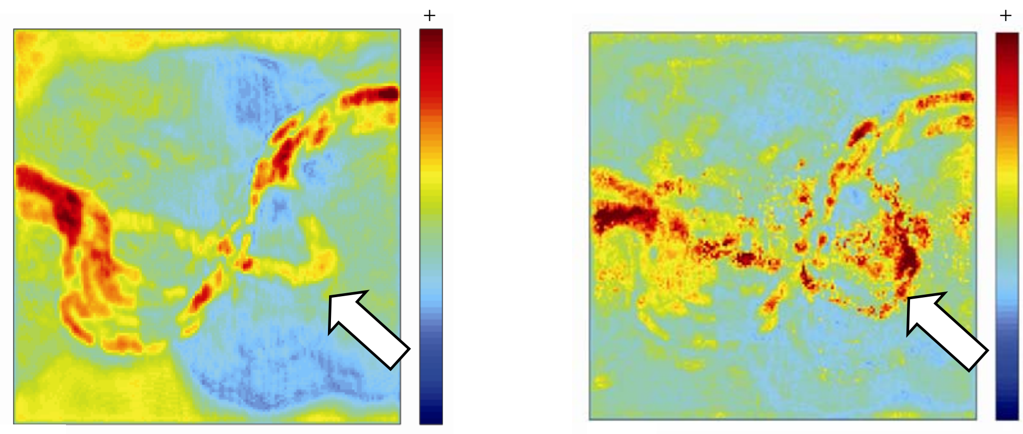


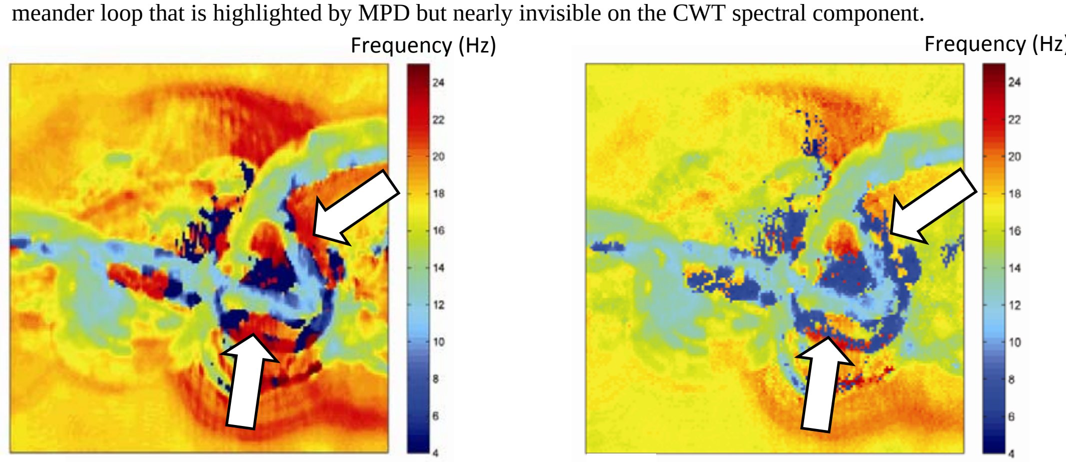
a). b).

Figure 4. Comparison of the 2nd principal component derived from (a) CWT and (b) MPD spectral components. Block arrows indicate regions of improved resolution achieved by MPD.



a). b).

Figure 5. Comparison of 5 Hz spectral components from (a) CWT and (b) MPD. Block arrows indicate a meander loop that is highlighted by MPD but nearly invisible on the CWT spectral component.



a). b).

Figure 6. Comparison of peak frequency horizons extracted from (a) CWT and (b) MPD spectral components. Block arrows indicate a low frequency channel meander that is more distinct and continuous on MPD than CWT.

EDITED REFERENCES

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