Resolving subtle stratigraphic features using spectral ridges and phase residues

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Abstract

Seismic interpretation is dependent on the quality and resolution of seismic data. Unfortunately, seismic amplitude data are often insufficient for detailed sequence stratigraphy interpretation. We reviewed a method to derive high-resolution seismic attributes based upon complex continuous wavelet transform pseudodeconvolution (PD) and phase-residue techniques. The PD method is based upon an assumption of a blocky earth model that allowed us to increase the frequency content of seismic data that, for our data, better matched the well log control. The phase-residue technique allowed us to extract information not only from thin layers but also from interference patterns such as unconformities from the seismic amplitude data. Using data from a West Texas carbonate environment, we found out how PD can be used not only to improve the seismic well ties but also to provide sharper sequence terminations. Using data from an Anadarko Basin clastic environment, we discovered how phase residues delineate incised valleys seen on the well logs that are difficult to see on vertical slices through the original seismic amplitude.

Introduction

Fourier spectral analysis is a key component of seismic data processing. Random and coherent noise filtering, spectral balancing, wavelet shaping, and Q compensation are all based on spectral analysis. Spectral analysis techniques are also useful in seismic interpretation. Using a running window spectral analysis, also called a short window discrete Fourier transform (SWDFT), Partyka et al. (1999) compute the spectra for overlapping windows thereby producing a 4D time-frequency data volume. These 4D frequency data volumes can be used to detect lateral changes in thickness. In addition to the SWDFT, one can use transforms based on a library of wavelets, giving rise to the continuous wavelet transform (CWT) (e.g., Stockwell transforms) and matching pursuit algorithms (Castagna et al., 2003).

Taner et al. (1979) introduce complex trace attributes such as quadrature, envelope, phase, and instantaneous frequency, attributes that are well known among the geophysical community. Taner et al. (1979) note that the instantaneous frequency \( f \) suffered discontinuities associated with abrupt changes in phase, which in turn were associated with waveform interference located at envelope \( e \) minima. To remove these discontinuities, Taner et al. (1979) introduce a weighted average frequency \( f_{avg} \) at time \( t = k\Delta t \) as

\[
f_{avg} = \frac{\sum_{j=-K}^{+K} e_{k-j} f_{inst}^{j}}{\sum_{j=-K}^{+K} e_{k-j} L_{j}},
\]

where \( e \) is the envelope (also called the reflection strength), \( f_{inst} \) is the instantaneous frequency, and \( L \) is a low-pass filter.

Combining the concepts of instantaneous and weighted average frequency, Taner (2000) introduces a thin-bed indicator attribute by removing the weighted average frequency from the instantaneous frequency thereby enhancing zones in which wavelet destructive interference takes place. The thin-bed indicator is given by

\[
f_{thin} = f_{inst} - f_{avg}.
\]

These zones of destructive interference are referred to as frequency spikes. In Figure 1, we show an example of the instantaneous frequency, weighted average frequency, and thin-bed indicator attributes.

Zeng (2010) uses synthetic models and field data to correlate frequency spikes with geologic information, defining two types of frequency spikes. Type I spikes are related to the destructive interference of the top and base layer reflection of a wedge. Type II spikes are more indicative of thin beds. Zeng (2010) shows

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type II spikes occur at wavelengths less than one-fifth of a wavelength (Figure 2).

Li and Liner (2008) introduce a technique based on the Hough transform to detect singularities in the CWT magnitude spectra. Using Li and Liner’s (2008) algorithm, Smythe et al. (2004) show that discontinuities in the CWT of the underlying impedance model are preserved as discontinuities seen in band-limited seismic amplitude data.

In general, seismic data amplitudes are not as well preserved as seismic phases. Matos et al. (2011) therefore introduce an alternative spectral discontinuity method based on the phase of the CWT components. Because instantaneous frequency is the time derivative of the instantaneous phase, there is a direct relationship between Matos and Marfurt (2011) phase discontinuity and earlier work by Taner (2000) and Zeng (2010). Likewise, there is a similarity between (Matos and Marfurt, 2011) pseudodeconvolution (PD) and “spectral whitening” deconvolution operators implemented in the frequency domain.

We begin our paper with a review of spectral decomposition to generate PD and phase residues attributes.

**Figure 1.** Vertical slices through (a) instantaneous frequency \( f_{\text{inst}} \), (b) envelope weighted average frequency, \( f_{\text{avg}} \), and (c) thin-bed indicator, \( f_{\text{thin}} = f_{\text{inst}} - f_{\text{avg}} \) obtained as the difference between the (a and b). (c) Is plotted using a color bar that highlights the extreme values (after Taner, 2000).

**Figure 2.** Zeng’s (2010) (a) seismic amplitude and (b) corresponding instantaneous frequency from a three-layer model giving rise to a reflector coefficient of \(-R\) and \(+R\) for the first and second interface. Note the “type I” spikes within the center layer. (c) Seismic amplitude and (d) corresponding instantaneous frequency for a seven-layer model giving rise to a suite of \(-R, +R, -R, +R, -R, +R, +R\) reflection coefficients between interfaces. On these models, two types of frequency spikes can be identified. (b) Zeng (2010) defines the anomaly observed at the center of the model as a type I spike. Note that the spike appears at wavelengths larger than tuning wavelength. (d) Zeng (2010) finds that type II spikes are associated with thin beds, they depend on the impedance contrast of the layers, and the predominant wavelet frequency in which they occur is inversely proportional to the thickness of the beds.
We then apply these methods to a carbonate system from West Texas and show how these algorithms can help accelerate interpretation of thin reflectors. Then, we apply these algorithms to a Red Fork incised valley system from the Anadarko Basin and show how phase residues correlate to sequence boundaries seen on logs. We conclude with a discussion of assumptions, processing workflows, and limitations associated with these two attributes.

**Methodology review**

**Spectral ridges and PD**

The CWT is the crosscorrelation between the seismic trace and dilated versions of a symmetric “mother” wavelet (Grossman and Morlet, 1984). Because the mother wavelet is symmetric, we can compute the CWT by convolving the seismic trace with the time-reversed scaled version of the basic wavelet (Figure 3c). Because convolution in the time domain is equivalent to multiplication in the frequency domain, we can also interpret the CWT as a suite of band-pass filters resulting in spectral components. Each seismic trace is represented by a time (depth) versus frequency band (or scale) complex matrix. This matrix represents how well the seismic trace correlates to each dilated wavelet at each instant of time (Matos and Marfurt, 2011).

Mallat and Zhong (1992) show that the CWT ridges along the frequency bands are associated with signal inflection points that characterize much of the signal (Figure 3d). They also show that we can reconstruct a nonunique but very good approximation of the seismic trace by using only the CWT ridges (Figure 3e), which they call wavelet transform modulus maxima line amplitudes (WTMMLAs). Tu and Hwang (2005) later prove that the same concept can be applied using complex wavelets. Grossman and Morlet (1984) show that the complex CWT magnitude represents the average magnitude of each spectral component (dilated wavelet) at each instant of time. Likewise, the maximum averages, or the ridges, along the scales (WTMMLA) show the existence of consistent signal transitions.

Borrowing CWT spectral ridge (WTMMLA) ideas from Mallat and Zhong (1992) and Tu and Hwang (2005), several authors show how CWT spectral ridges...
can be associated with a reflectivity series (Hermann and Stark, 2000; Li and Liner, 2008; Devi and Schwab, 2009; Matos and Marfurt, 2011). Matos and Marfurt (2011) show how to enhance seismic resolution by using complex Morlet CWT spectral ridges and reconstructing the seismic trace using broader band wavelets than those used in the original analysis giving a result they call PD. This process is schematically shown in Figure 3.

Figure 4a shows a single 2D synthetic seismic response of a channel with thicknesses varying from 0 to 50 ms. Figure 4b shows the PD result. We can clearly see the improvement in the seismic resolution. Figure 4c shows the relative acoustic impedance (RAI) computed from Figure 4b. This high-resolution seismic representation can be considered a reflectivity approximation, which can be integrated to estimate the RAI (Bertusssen and Ursin, 1983). The RAI computation consists of three steps:

1) rescale the high-resolution trace by keeping the magnitude much smaller (we suggest 10 times) than one
2) integrate the trace using the procedure designed by Peacock (1979) for discrete integration
3) high-pass filter (we suggest \( f > 10 \) Hz) the integrated data to provide RAI.

We assume that the earth impedance model is blocky, thus giving rise to a suite of sparse spikes that we convolve with a narrowband seismic wavelet giving rise to conventional seismic data. We can replace these wavelets frequency by frequency with their broadband equivalents, thereby generating a broadband signal. The process relies on the original frequency information of the narrowband wavelets; hence, the frequencies not sampled will not be reconstructed. We validate all these assumptions by tying the broadband data to well synthetic seismograms.

**Figure 5.** (a) Amplitude from a three-layer synthetic wedge model. Corresponding CWT spectral magnitude response at (b) 15, (c) 30, and (d) 70 Hz and phase response at (e) 15, (f) 30, and (g) 70 Hz. We identify phase anomalies in the spectral phase (white arrows) and magnitude (black arrows). This is the phenomena that is first described by Ghiglia and Pritt (1998). Note that the anomaly location is frequency dependent.
Figure 6. (a) Three-layer synthetic wedge model shown previously in Figure 5, (b) corresponding instantaneous frequency exhibiting type I and type II discontinuities, and (c) phase residue, where the color indicates the frequency at which the residue (discontinuity) occurs. Anomalies on (b) and (c) occur at the same wedge thicknesses and are generated by the same interference pattern in the data. (b) The gray arrow indicates a type I spike, and the white arrow indicates type II spikes (Zeng, 2010). (d) Phase residues give a more continuous anomaly allowing it to be more easily mapped.

Figure 7. (a) Map displaying the location of the Diamond M field in Scurry County, Texas (modified from Pennel and Melzer, 2003). (b) Time structure map along the top reef pick showing the location of line A-A’.
Figure 8. Well 2 synthetic seismogram using the seismic amplitude data. The correlation was done using a 250-ms window centered at 870 ms. The correlation coefficient is 68%. The green marker in the synthetic window corresponds to the top of the Horseshoe Atoll reef. Note that the extracted wavelet is minimum phase.

Figure 9. Well 2 synthetic seismogram using the PD data. The correlation was done using a 250-ms window centered at 870 ms. The correlation coefficient is 79%. The green marker in the synthetic window corresponds to the top of the Horseshoe Atoll reef. Note that the extracted wavelet is zero phase.
**Spectral discontinuities and phase residues**

Although the complex CWT phase can be used to reconstruct the high-resolution trace, Bone (1991) shows that a shifted and dilated wavelet can interfere with another wavelet creating a signature in the phase spectra. This interference or inconsistency is called a phase residue. Matos et al. (2011) show how one can detect phase discontinuities in the Morlet complex wavelet transform phase component. They implement the technique that Ghiglia and Pritt (1998) develop for detecting phase anomalies using a rectangular window and looking for inconsistent phase values when unwrapping these phase components. Matos et al. (2011) use phase residues to map wavelet interference patterns that correlate with stratigraphic discontinuities as well as inconsistencies in seismic data quality. To demonstrate this concept, we generated a three-layer synthetic wedge model embedded in a shale background. We used a Ricker wavelet with a peak frequency of 46 Hz and 100 ms length. In Figure 5, we show the spectral magnitude and spectral phase for 15-, 30-, and 70-Hz frequencies for our wedge model. We are able to identify the phase discontinuities that Ghiglia and Pritt (1998) describe within each magnitude-phase pane for each frequency. Figure 6 shows the phase residues generated using the model shown in Figure 5.

Note that the discrete type I and type II spikes seen in Figure 6 appear as a more continuous anomaly in the phase residue seen in Figure 6c, allowing one to track the discontinuity laterally. Cohen (1993) shows that instantaneous attributes estimate the average properties of the seismic wavelet, such as the instantaneous frequency of an isolated wavelet. Note that type I and type II discontinuities appear at approximately 60 Hz (green). Examining Figure 6c, we note the phase residue at these two locations also occurs at 60 Hz (green).

**Figure 10.** Cross section A-A’ displaying wells 1 and 2 converted to time using the time to depth relationship from the PD seismic well tie (Figure 9). (a) Although the time to depth relationships were created using the PD data, these relationships work well with the seismic amplitude data too. Log curves on the wells are gamma ray (black), bulk density (red), and neutron porosity (blue). The gamma ray values increase to the left, and the bulk density and neutron porosity values increase to the right. (b) PD data cross section A-A’ displaying wells A and B converted to the time to depth relationship from the PD seismic well tie (Figure 9). With the PD data, it is easier to identify onlaps, toplaps, downlaps, and reflector truncations than with the seismic amplitude data. (c) PD data cross section A-A’ zoomed on the clinoform interval. Black arrows indicate downlap or onlap features identified in the internal structure of the clinoform. On well 2, we identify a highstand to transgressive system track sequence (green arrow) that correlates with our onlap and downlap features. Note that the same event is not identified on well 1, indicating that well 1 is closer to the shelf. (d) Seismic amplitude data cross section A-A’ zoomed on the clinoform interval. Besides the onlap features close to well 1, it is difficult to identify any other clear reflector terminations in the seismic amplitude data.
Figure 11. (a) RAI volume probe with all voxels in the probe plotted as opaque. We will use opacity on the histogram to isolate the response of the top (magenta) and base (red) of the prograding sequence shown in Figure 10. Note that the clinoform has a distinctive response being delimited by the highest and lowest values of RAI. (b) Setting the low-amplitude voxels as opaque isolates the top boundary of the clinoform. (c) Setting the high-amplitude voxels as opaque isolates the bottom boundary of the clinoform. We use these two geobodies as input for our seismic interpretation.

Figure 12. (a) Using the geobody extraction shown in Figure 11b and 11c, we convert the top and bottom of the prograding sequence to the green and yellow seismic horizons. We interpret the green horizon as a maximum flooding surface (MFS) and the yellow horizon as a sequence boundary (SB). This interpretation is corroborated by the results found in Figures 10 and 11. (b) Comparison of the RAI volume to the acoustic impedance log from wells 1 and 2. The AI log decreases to the right. At the zone of interest, the acoustic impedance log shows an excellent correlation with the RAI attribute, demonstrating that the RAI algorithm is reliable, and it can be used in frontier zones where wells are not present to delineate zones of interest.
Rather than probing for discontinuities at the average frequency, the phase residue algorithm probes at a suite of frequencies on CWT spectral components, thereby giving rise to a laterally continuous anomaly.

Comparing Figures 4 and 6, we see the complementary nature of CWT phase residues, high-resolution spectral ridges and RAI and their potential use in seismic interpretation. Specifically, spectral ridges enhance individual reflectors, whereas phase residues enhance unconformities and pinch-outs.

Application of CWT attributes to improve reservoir geometry interpretation

**Carbonate environment example (Midland Basin, TX)**

The Diamond M data set consists of approximately 25 mi$^2$ of seismic data with a high signal-to-noise ratio located in Scurry County, TX (Figure 7). We computed the PD and RAI attributes to determine if they better define the stratigraphic sequences of interest. Figure 7 shows the location of the composite seismic line and the location of two wells used for the interpretation. Figures 8 and 9 show representative synthetic seismograms used to tie well data to the original seismic data and PD data, respectively. The original data show a minimum phase character, whereas the bandwidth extension process not only enhances the resolution of the data but also converts it to zero phase. Examining composite line AA’ we compare the original seismic data with the PD data in our integrated interpretation with the well data (Figure 10). We identify reflector terminations on Figure 10b in the vicinity of well 2 that on Figure 10a appear as a continuous reflector. Further evaluation using the well logs allows us to interpret the sequence as a highstand to transgressive systems track progression (Figure 10c). We compared the PD and seismic amplitude data and found that the PD data shows a better defined progradational sequence with internal onlap and downlap terminations for the identified sequence (Figure 10c–10d). We proceed to evaluate the RAI character of this clinoform using a seismic probe, and we are able to extract the top and the base of the clinoform sequence and convert them to seismic

![Figure 13](https://example.com/figure13.png)

*Figure 13.* (a) Location of the Watonga data set in the Anadarko Basin, OK (after Peyton et al., 1998). (b) Representative horizon through seismic amplitude at the top Pink Lime indicating the location of composite line AA’. (c) Red Fork incised valley stages I through V (after Peyton et al., 1998).
horizons (Figure 11). We display our RAI-created horizons on the original seismic data and the PD (Figure 12a) data and corroborate that the top and base horizons correspond to the previously identified highstand systems tract sequence. Finally, we compare the RAI result to the acoustic impedance (AI) log finding a strong correlation (Figure 12b). This result demonstrates the reliability of the RAI using the CWT method in areas where little or no well control is available. Equally important, generating the horizons using PD, RAI, and geobody extraction took 30 minutes versus 3 hours using the conventional autotracker seismic interpretation.

**Clastic environment example (Anadarko Basin, OK)**

Red Fork sands are a prominent gas producer in the Anadarko Basin. The Red Fork stratigraphy consists of...

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**Figure 14.** (a) Stratigraphic well log cross section A-A’. Based on the well log data and the interpreted well tops, we define five incision stages on the Red Fork formation. This interpretation is similar to that of Peyton et al. (1998). (b-d) Zoomed portions of A-A’ cross section. Data and cross-section interpretation are courtesy of M. Falk and A. Warner, Chesapeake Energy Corp.
regional deltaic deposits that endured five stages of fluvial incision during a sea-level low stand. Such fluvial incisions are informally called *invisible channels* because they cannot be identified on stacked seismic data but are encountered by subsequent drilling to deeper targets (Peyton et al., 1998; Suarez et al., 2008; Barber, 2010).

Figure 13 shows a map with the location of the seismic data of the Watonga field, well locations, and composite line locations and the Peyton et al. (1998) interpretation of the Red Fork incised valleys using semblance, 30-Hz spectral magnitude, and well data. Collaborating with Chesapeake Energy geoscientists, we show an updated version of Peyton et al.’s (1998) cross-section AA’ using the exact same well data (Figure 14). Figures 15 and 16 show the synthetic seismograms for wells R and S, respectively. These are the only wells with sonic and density logs in the survey. Well R penetrates the regional Red Fork sequence. Well S penetrates incision stage V. Time to depth curves differ depending on the geologic section that a well penetrates. We found that wells that penetrate the regional Red Fork share a similar time to depth relationship, whereas wells that penetrate any of the incision stages share a different time to depth relationship. By using these two different time to depth curves, we were able to tie most

**Figure 15.** Well R synthetic seismogram using the seismic amplitude data. The correlation was done using a 250-ms window centered at 1800 ms. The correlation coefficient is 70%. Orange marker corresponds to the Oswego Limestone. The yellow marker corresponds to the Inola Limestone, and the green marker in the synthetic window corresponds to the top of the Novi Limestone.

**Figure 16.** Well S synthetic seismogram using the seismic amplitude data. The correlation was done using a 300-ms window centered at 1800 ms. The correlation coefficient is 70%. The orange marker corresponds to the Oswego Limestone. The pink marker corresponds to the base of the Pink Lime, and the green marker in the synthetic window corresponds to the top of the Novi Limestone.
wells on Peyton et al.’s (1998) AA’ cross section with our seismic amplitude and phase residue data. Composite line AA’ through the seismic data shows one of these incisions (Figure 17). Once we tied all the wells in Figure 14 with the seismic data, we compared the well tops from the regional Red Fork and the incision stages with anomalies observed in the seismic data. In the seismic amplitude section, we are able to correlate only the Pink Lime, Inola Limestone, and stage V tops (Figure 17b and 17c). Using phase residues and the regional Red Fork and incision stage tops from Figure 14, we not only identify the stage V incision as in Figure 17, but we are also able to identify two additional phase residue anomalies that correspond to the other stages of incision that were invisible on the seismic data (Figure 18b and 18c). We proceed to interpret the phase

**Figure 17.** Vertical section AA’ through (a) seismic amplitude data, (b) seismic amplitude data with Pink Lime (pink horizon) and Inola Limestone (blue horizon) interpreted on the seismic amplitude data using the guidance from the well-top data, and (c) interpreted seismic amplitude data with incision stages well-tops overlaid. (a) We are able to identify incision stage V between wells S and U, but stages I-IV are invisible on the seismic amplitude data. (b) We interpreted the Pink Lime and Inola Limestone (pink and blue horizons, respectively) and posted the interpreted tops for the same surfaces in each well to corroborate our interpretation. (c) By posting the interpreted incision stages surfaces for the well data, we corroborate that stages I-IV of incision are invisible on seismic vertical sections.

**Figure 18.** Vertical section AA’ through (a) phase residues attribute, (b) phase residues with regional Red Fork the well-top data posted, and (c) phase residues with incision stages well tops posted. (a) On the phase residues attribute we identify anomalies that resemble channel like features. (b-c) We corroborate that some of the anomalies seen in (a) match the interpreted regional Red Fork (diamond shapes) as well as the incision stages (square shapes) from the well logs.
residues attribute in a conventional way and generate surfaces from the Pink Lime and stages I–V (Figure 19). Using these interpreted surfaces, we create a 3D geocellular model and compare it to Peyton et al.’s (1998) original interpretation (Figure 20). Figure 21 shows a 3D perspective of the regional Red Fork and each incision stage. Each stage occurred in a different depositional environment with stage I having lag deposits and

**Figure 19.** Vertical section AA' through (a) seismic amplitude data, (b) instantaneous frequency, (c) phase residues, and (d) seismic amplitude correndered with phase residues. (b) We are able to identify the anomaly generated by stage V in the instantaneous frequency. (c) We interpreted the anomalies that matched the incision stages as well as the Pink Lime and the Inola Limestone. We generated surfaces from the five interpreted horizons to create a geologic model.

**Figure 20.** (a) Red Fork incised valley stages I through V interpretation from Peyton et al. (1998). (b) Resulting 3D geologic model from well, seismic amplitude, and phase residues data integrated seismic interpretation. (b) We obtained a 3D model that matches the Peyton et al. (1998) original interpretation on spectral magnitude phantom horizon. (b) The green arrow is pointing north.
stage V filled by a shale plug (Suarez et al., 2008). Separating each stage from the regional Red Fork facilitates geologic modeling each stage to estimate reservoir properties consistent with the depositional environment.

Conclusions
Spectral analysis has long been used in seismic processing and interpretation. We have demonstrated how CWT PD, RAI, and phase residues can be effectively applied to reveal and enhance stratigraphic features that are buried in conventional seismic amplitude data. PD enhances reflector terminations, facilitating seismic sequence stratigraphy interpretation. RAI computed from PD, when used as a geobody extraction and interpretation tool, accelerates the interpretation of clinoforms and complex features. Phase residues extends the well established thin bed indicator and instantaneous frequency spike interpretation workflows, providing more continuous discontinuities, as well as the magnitude and frequency at which they occur. We have developed a workflow that combines seismic amplitude with CWT attributes to produce a high-frequency seismic stratigraphy framework for seismic interpretation. Finally, we have demonstrated how by combining CWT attributes with detailed seismic stratigraphy, sequences can be extracted from the seismic data as an input for detailed reservoir characterization.

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