Coherence attribute applications on seismic data in various guises — Part 2

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Abstract

We have previously discussed some alternative means of modifying the frequency spectrum of the input seismic data to modify the resulting coherence image. The simplest method was to increase the high-frequency content by computing the first and second derivatives of the original seismic amplitudes. We also evaluated more sophisticated techniques, including the application of structure-oriented filtering to different spectral components before spectral balancing, thin-bed reflectivity inversion, bandwidth extension, and the amplitude volume technique. We further examine the value of coherence computed from individual spectral voice components, and alternative means of combining three or more such coherence images, providing a single volume for interpretation.

Introduction

Although most seismic data are processed to maximize the bandwidth, some form of spectral balancing on the seismic data prior to attribute computation almost always helps in enhancing more subtle attribute anomalies. Most spectral-balancing algorithms assume the underlying reflectivity to be random, such that balancing removes the spectral contribution of the seismic wavelet, with resulting frequency anomalies more closely associated with tuned reflections that occur at layers exhibiting quarter-wavelength thickness. Partyka et al. (1999) and Marfurt and Kirlin (2001) use spectral decomposition to quantify such tuning effects on 3D seismic data volumes. Partyka et al. (2005) show spectral magnitude components \( a(f) \) to be effective in mapping lateral changes in vertical thickness, and they show spectral phase components \( \varphi(f) \) to be effective in mapping faults and stratigraphic edges. Spectral voice components, \( v(f) \equiv m(f) \exp[i\varphi(f)] \), are less commonly used by interpreters, but they often provide additional insight into subsurface features (Fahmy et al., 2008; Chopra and Marfurt, 2016). Going one step further, coherence computed from such spectral voice components can highlight discontinuities that are preferentially imaged by a given spectral component. Although the analysis of multiple spectral components is common when restricted to a specific geologic target, the generation of 10–20 coherence volumes computed from a suite of spectral components prescribes simple analysis tools such as animation and interactive corending for a large 3D seismic volume as a whole. Our goals therefore are to (1) determine what additional information is provided by coherence volumes computed from narrowband spectra and (2) evaluate alternative ways to combine such multiple images into a single volume. Because different spectral components are sensitive to different scales of discontinuities, the challenge is to analyze these volumes effectively. Alternative methods that can be used for this purpose include using color, principal component analysis (PCA), self-organizing maps (SOMs), and multispectral coherence. We discuss three of these methods in this paper, leaving the SOM method for discussion in another paper.

Integration of coherence and spectral decomposition

Spectral decomposition

In its simplest implementation, one can compute spectral components through the application of a suite of band-pass filters (often called filter banks) to the original seismic amplitude data. The interpretation value of a given spectral component is a function of the tuning thickness of a given geologic target and by the signal-to-noise ratio at that frequency. However, phase is also important, as demonstrated by Libak et al. (2017), who show that the lack of a coherence anomaly along a clearly discernable fault is often due to the unfortunate alignment of peaks and troughs of different reflectors across the fault. Such phase-alignment changes with frequency allow for improved fault imaging. Smaller, vertically localized faults are often best

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Manuscript received by the Editor 5 January 2018; published ahead of production 24 March 2018; published online 29 June 2018; Repaginated version published online 6 August 2018. This paper appears in Interpretation, Vol. 6, No. 3 (August 2018); p. T531–T541, 8 Figs.
examined at the reflector tuning frequency, whereas larger, through-going faults are commonly seen through by a broad range of frequency components. There are several spectral decomposition algorithms available to the seismic interpreter, each with its advantages and disadvantages. For a comparison, we refer the reader to Leppard et al. (2010), who find matching pursuit algorithms to provide improved vertical resolution over the computationally more efficient continuous wavelet transform, S-transform, and simple discrete Fourier transform algorithms. Puryear et al. (2012) constrained least-squares algorithm provides further spectral resolution; however, this improved resolution results in abrupt changes from finite-valued to zero-valued spectral components on neighboring traces, which result in unwanted coherence artifacts.

**Damage zones**

Accurate imaging of fault damage zones has become increasingly important in seismic exploration, particularly in shale resource plays, where such faults can significantly increase permeability but also introduce difficulties in geosteering. Depending on the play, such damage zones may connect to nearby aquifers and produce water, produce high-sulfur gas from nearby salt layers, or produce large volumes of gas from more distant, more mature parts of the play. Liao et al. (2017) use a reprocessed megamerge survey composed of multiple legacy 3D seismic surveys to map the damage zone about a large strike-slip fault associated with the Oklahoma Au lacogen. Using 3D seismic attributes, they image not only the main strike-slip faults, but also the Riedel shears and rhombochasms.

**Figure 1.** Stratal slices just above the top Hunton limestone (base Woodford shale) through spectral magnitude components generated at approximately (a) 20, (b) 30, (c) 40, (d) 50, (e) 60, and (f) 70 Hz. Lineaments corresponding to major strike-slip faults are well delineated at lower frequencies (yellow arrows), whereas finer lineaments corresponding to Riedel shears are better delineated at higher frequencies (white arrows). The white ellipses indicate two rhombochasms that will be seen in later figures (data courtesy of TGS, Houston).
In this paper, we examine a different portion of this strike-slip fault system imaged by a modern wide-azimuth survey acquired by TGS in 2015. In Figures 1 and 2, we show an equivalent suite of time slices through corresponding spectral magnitude and phase volumes, respectively. These spectral magnitude displays indicate an abundance of lineaments, although their definitions may not be very clear for all of them. Figure 3 shows the coherence attribute computed on the spectral magnitude volumes. Each of the displays exhibits abundance discontinuity detail, including two major strike-slip faults (yellow arrows), Riedel shears (cyan arrows), and two rhombochasms (red ellipses). However, many areas of these images appear defocused (green ellipses).

**Voice components**

In Figure 4, we show a suite of time slices through the real voice component volumes ranging from 20 to 70 Hz corresponding to the magnitude components shown in Figure 1. In addition to the spectral and phase components, Goupillaud et al. (1984) describe the voice component, which is a simple function of spectral magnitude $a_m$ and phase $\phi_m$ at each time-frequency sample for trace $m$ and is given by

$$a_m(t, f) = a_m(t, f) \cos[\phi_m(t, f)].$$  \hspace{1cm} (1)

Our implementation of energy-ratio coherence is based on the analytic trace, such that the Hilbert transform of equation 1 is also used:

**Figure 2.** Stratal slices just above the top Hunton limestone (base Woodford shale) through spectral phase components generated at approximately (a) 20, (b) 30, (c) 40, (d) 50, (e) 60, and (f) 70 Hz. Lineaments corresponding to major strike-slip faults are well-delineated at lower frequencies (yellow arrows), whereas finer lineaments corresponding to Riedel shears are better delineated at higher frequencies (white arrows). The black ellipses indicate two rhombochasms that will be seen in later figures (data courtesy of TGS, Houston).
The real part of the sum over all frequencies \( f \) of all these voice components reconstructs the original trace. Figure 5 shows a stratal slice through the energy-ratio coherence computed from the spectral components. Comparing the 20 Hz component of Figures 3 and 5, we notice considerably more detail in Figure 3a, but with some of these features mimicking the rugose topography of the top Hunton limestone. In contrast, Figure 4a seems to delineate only the major fault and several of the larger Riedel shears. Examining coherence computed from the 50 Hz component shown in Figures 3d and 5d, we notice the improved lateral resolution of the image computed from the spectral real and Hilbert transform of the spectral voices, where the discontinuities are consistent with our strike-slip deformation model described by Liao et al. (2017) using clay models and a nearby seismic data volume. By ignoring the phase component of the seismic data, coherence computed from the spectral magnitudes appears to introduce “structural leakage” or other mixing artifacts into the image (the green ellipses in Figure 3e and 3f) that do not appear in the coherence images computed from the voice components (Figure 5e and 5f). Figure 3g shows the stratal slice though coherence computed from the original (broadband) seismic data volume. Careful comparison shows increased structural detail in the coherence images computed from spectral voices in the areas indicated by the green ellipses, which

\[
a^H_m(t,f) = a_m(t,f) \sin[\phi_m(t,f)].
\]  

(2)
we interpret to be associated with smaller, vertically limited Riedel shear zones.

**Principal component analysis**

PCA is a useful statistical technique that has found many applications, including image compression and pattern recognition in data exhibiting high dimensionality. Interpreters are familiar with the usual statistical measures, such as mean, standard deviation, and variance, which are essentially 1D. Such measures are calculated one attribute at a time with the assumption that each attribute is independent of the others. In reality, many of our attributes are coupled through the underlying geology, such that a fault may give rise to lateral changes in waveform, dip, peak frequency, and amplitude. Less desirably, many of our attributes are coupled mathematically, such as alternative measures of coherence (Barnes, 2007) or of a suite of closely spaced spectral components. The amount of attribute redundancy is measured by the covariance matrix. The first step in multiattribute analysis is to subtract the mean of each attribute from the corresponding attribute volume. If the attributes have radically different units of measure, such as frequency measured in Hertz, envelope measured in milliVolts, and coherence without dimension, a Z-score normalization is required. The element $C_{mn}$ of an $N$ by $N$ covariance matrix is then simply the cross-correlation between the $m$th and $n$th scaled attribute over the volume of interest. Mathematically, the number of linearly independent attributes is defined by the value of eigenvalues and eigenvectors of the covariance matrix.

![Figure 4](image-url)

**Figure 4.** Stratal slices just above the top Hunton limestone (base Woodford shale) through spectral voice components generated at approximately (a) 20, (b) 30, (c) 40, (d) 50, (e) 60, and (f) 70 Hz. Lineaments corresponding to major strike-slip faults are well-delineated at lower frequencies (yellow arrows), whereas finer lineaments corresponding to Riedel shears are better delineated at higher frequencies (cyan arrows). The purple ellipses indicate two rhombochasms that will be seen in later figures (data courtesy of TGS, Houston).
The first eigenvector is a linear combination that represents the most variability in the scaled attributes. The corresponding first eigenvalue represents the amount of variability represented. Commonly, each eigenvalue is normalized by the sum of all the eigenvalues, resulting in a percentage of the variability represented.

Although the computation of multiattribute eigenvectors and eigenvalues does not provide the same physical insight into the data as multiattribute display, it does reduce the number of attributes used for subsequent analysis. For this reason, PCA is the first step in “fancier” clustering techniques such as SOMs, generative topographic maps, and support vector machine analysis. Dewett and Henza (2016) use SOM to combine multispectral images of coherence into a single volume. We will apply similar clustering workflows to this data volume in a future paper.

By convention, the first step is to order the eigenvalues from the highest to the lowest. The eigenvector with the highest eigenvalue is the principal component of the data set (PC1); it represents the vector with maximum variance in the data and also represents the bulk of the information that would be common in the attributes used. The eigenvector with the second-highest eigenvalue, called the second principal component, exhibits lower variance and is orthogonal to PC1. PC1 and PC2 will lie in the plane that represents the plane of the data points. Similarly, the third principal component (PC3) will lie in a plane orthogonal to the plane of the first two principal components. In the case of \( N \) truly random attributes, each eigen-

![Figure 5](image-url)

**Figure 5.** Stratal slices just above the top Hunton limestone (base Woodford shale) through coherence volumes computed from the spectral voice components shown in Figure 2 at (a) 20, (b) 30, (c) 40, (d) 50, (e) 60, and (f) 70 Hz. Note the improvement in fault delineation in the areas indicated by the green ellipses. The arrows and red ellipses indicate the same features shown in the previous figures (data courtesy of TGS, Houston).
value would be identical and equal to $1/N$. Because seismic attributes are correlated through the underlying geology and the band limitations of the source wavelet, the first two or three principal components will almost always represent the vast majority of the data variability.

Saleh and de Bruin (2000) demonstrate the extraction of amplitude-variation-with-offset (AVO) attributes from distorted offset-dependent amplitudes, and they go on to show that these attributes were more robust displaying improved ability to identify fluid effects. Tingdahl and Hemstra (2003) discuss the estimation of fault orientation using PCA on seismic attributes such as dip, azimuth, coherence, or meta-attributes derived from the others. All the considered attributes have a common property in that they have high values at the position of the faults and exhibit low values elsewhere. Singh (2007) discusses the application of PCA on AVO-derived attributes for lithofacies discrimination and fluid detection.

Guo et al. (2009) compute 86 spectral components ranging from 5 to 90 Hz using a matching pursuit technique described by Liu and Marfurt (2007). Next, PCA was performed on the 86 spectral components by forming an $86 \times 86$ covariance matrix. Thereafter, the covariance matrix is decomposed into 86 eigenvalue-eigenvector pairs. They find that the first three components account for most of the spectral variance seen along the horizon of interest, with the remaining components accounting for approximately 17% of the data variance. This way, the dimensionality reduction was brought down from 86 to 3.

We apply PCA to the generated voice component coherence volumes at 20, 30, 40, 50, 60, and 70 Hz, and we examine the first principal component volume. A stratal slice display equivalent to the other displays shown in Figures 1–4 is shown in Figure 6. Note that the first PCA component has captured most of the discontinuity detail in the individual voice components, although the lineaments do not show up as crisp as seen on some of the individual voice component displays.

**RGB color blending**

Color blending of three data sets, one with red, another with green, and the third with blue, is an effective way of integrating the information in the individual data sets for ease in comparison, viewing, and hence interpretation. Leppard et al. (2010) and Henderson et al. (2008) provide excellent examples of effective RGB color blending used to represent three spectral components. In contrast, Li and Lu (2014) and Honorio et al. (2017) compute coherence on different voice components and combine them using RGB color blending. In Figure 7, we show a color-blended image for three different energy-ratio coherences on voice component volumes (40 Hz in red, 50 Hz in green, and 60 Hz in blue). On this display, if the coherence at a given voxel’s three color channels is maximum, the blended color will be white, whereas if it is minimum, the blended color will be black. If the highest frequency coherence is lower than the others, there will be less blue in the image, resulting in yellow. In contrast, if the lowest frequency coherence image is lower, there will be less

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**Figure 6.** Stratal slices just above the top Hunton limestone (base Woodford shale) through the first principal component volume computed from the six coherence images shown in Figure 4. The yellow arrows indicate strike-slip faults, blue arrows Riedel shears, and red ellipses rhombochasms. This image captures most (though not all) of the features included on the six input coherence images, allowing the interpreter to work with a single, improved discontinuity volume (data courtesy of TGS, Houston).

**Figure 7.** Corendered coherence computed from 40, 50, and 60 Hz voice components shown previously as Figure 4c-4e. High coherence at all components appears as white, whereas low coherence at all components appears as black. Because lower coherence for a given component subtracts color, low coherence at 40 Hz appears as cyan, at 50 Hz as magenta, and at 60 Hz as yellow, clearly showing the contribution of the different spectral components (data courtesy of TGS, Houston).
Figure 8. Stratal slices just above the top Hunton limestone (base Woodford shale) through a suite of coherence volumes computed from the original broadband data (a) the original amplitude data after structure-oriented filtering, (b) the first derivative run on the data in (a), (c) second derivative run on the data in (a), (d) spectral balancing run on the original amplitude data using Helmore’s (2009) approach, (e) spectral balancing run on data in (a) using thin-bed reflectivity inversion, (f) spectral balancing using thin-bed reflectivity inversion run on data in (a) subsampled to half the original sample rate, (g) frequency bandwidth extension of data in (a) using thin-bed reflectivity inversion, and (h) AVT run on the data in (a). The top row shows broadband coherence, whereas the bottom row shows multispectral coherence computed from six voice components (data courtesy of TGS, Houston).
made in the previous figure red, resulting in cyan. Careful examination of the blended images quantitatively confirms the observation made in the previous figure — that different frequencies are more or less sensitive to different fault scales. Although effective, the limitation of this color display tool is that one is limited to showing only three components at a given time.

**Multispectral coherence**

Dewett and Henza (2016) address this limitation by computing energy-ratio coherence on a suite of voice components \(u(f)\) and combining the resulting images using SOMs. They then sharpen their faults using a commercial swarm intelligence algorithm.

Sui et al. (2015) address the multispectral coherence analysis problem by constructing a covariance matrix from the spectral magnitudes \(a_m\):

\[
C_{mn} = \sum_{l=1}^{L} \sum_{k=-K}^{K} [a(f_l, t_k, x_m, y_m)a(f_l, t_k, x_n, y_n)],
\]

where \(L\) is the number of spectral components. They find the resulting coherence images to be of higher quality than those computed from the broadband data, including most of the details seen in coherence computed by constructing covariance matrices from the individual magnitude components. By ignoring the phase component, they also find that the algorithm is less sensitive to structural dip, resulting in algorithmic simplification.

Marfurt (2017) builds on these ideas, but constructs a multispectral covariance matrix oriented along the structural dip using the analytic voice (equations 1 and 2) and therefore twice as many sample vectors (i.e., spectral voice components and their Hilbert transforms):

\[
C_{mn} = \sum_{l=1}^{L} \sum_{k=-K}^{K} [u(t_k, f_l, x_m, y_m)u(t_k, f_l, x_n, y_n) + u^H(t_k, f_l, x_m, y_m)u^H(t_k, f_l, x_n, y_n)].
\]

The corresponding energy-ratio coherence computed using this equation is then referred to as multispectral coherence. We demonstrate the application of this approach on the same 3D seismic data from central Oklahoma, USA. In Figure 8, we show a comparison of multispectral coherence computed on different versions of the data discussed in part 1 of this paper, with coherence computed from the original broadband seismic data. We notice that multicoherence displays exhibit more focused and distinct lineament detail in all the versions of the data that we have shown.

**Conclusion**

Positive and negative experiences in horizontal drilling through the Eagle Ford shale of South Texas and the STACK play of Central Oklahoma have resulted in an increased interest in damage zones. In this paper, we have evaluated alternative workflows to improve the detail of a damage zone illuminated by a modern wide-azimuth survey acquired over the SCOOP play of Central Oklahoma. This survey images not only many of the strike faults associated with the Oklahoma Aulacogen, but also the associated Riedel shears and rhombochams. Stratal slices along the base Woodford Shale show that

1) Spectral magnitude displays enhance the discontinuities in the data. Coherence on spectral magnitude highlights the discontinuities at different frequencies.
2) Coherence on voice components highlights the discontinuities at different frequencies that show better definition than coherence on the spectral magnitude, which can be helpful for their interpretation.
3) Combining different voice components using color is an effective way of combining the attribute volumes, but it is limited to three colors only.
4) PCA is an effective way of reducing the dimensionality in terms of the number of attributes we may use, and it is a useful option with the interpreter.
5) Multispectral coherence displays show crisper definition of lineaments and thus, most useful.

**Acknowledgments**

We wish to thank Arcis Seismic Solutions, TGS, Calgary for permission to present this work.

**References**


Satinder Chopra has 34 years of experience as a geophysicist specializing in processing, reprocessing, special processing, and interactive interpretation of seismic data. He has rich experience in processing various types of data such as vertical seismic profiling, well-log data, seismic data, etc., as well as having excellent communication skills, as evidenced by the many presentations and talks delivered and books, reports, and papers he has written. He has been the 2010–2011 CSEG distinguished lecturer, the 2011–2012 AAPG/SEG distinguished lecturer, and the 2014–2015 EAGE e-distinguished lecturer. He has published eight books and more than 400 papers and abstracts and likes to make presentations at any beckoning opportunity. His work and presentations have won several awards, the most notable ones being the EAGE Honorary Membership (2017), CSEG Honorary Membership (2014) and Meritorious Service (2005) Awards, 2014 Association of Professional Engineers and Geoscientists of Alberta (APEGA) Frank Spragins Award, the 2010 AAPG George Matson Award, and the 2013 AAPG Jules Braunstein Award, SEG Best Poster Awards (2007, 2014), CSEG Best Luncheon Talk Award (2007), and several others. His research interests focus on techniques that are aimed at the characterization of reservoirs. He is a member of SEG, CSEG, CSPG, EAGE, AAPG, and APEGA.

Kurt J. Marfurt received a Ph.D. (1978) in applied geophysics from Columbia University’s Henry Krumb School of Mines in New York, where he also taught as an assistant professor for four years. He joined the University of Oklahoma (OU) in 2007, where he serves as the Frank and Henrietta Schultz professor of geophysics within the ConocoPhillips School of Geology and Geophysics. He worked for 18 years in a wide range of research projects at Amoco’s Tulsa Research Center, after which he joined the University of Houston for eight years as a professor of geophysics and the director of the Allied Geophysics Lab. He has received the following recognitions: SEG best paper (for coherence), SEG best presentation (for seismic modeling), as a coauthor with S. Chopra best SEG poster (for curvature) and best AAPG technical presentation, and as a coauthor with R. Perez...
Altamar was honored with the best paper award in Interpretation (on a resource play case study). He also served as the SEG/EAGE distinguished short course instructor for 2006 (on seismic attributes). In addition to teaching and research duties at OU, he leads short courses on attributes for SEG and AAPG. He currently serves as the editor in chief of the SEG/AAPG publication Interpretation. His primary research interest is in the development and calibration of new seismic attributes to aid in seismic processing, seismic interpretation, and reservoir characterization. His recent work has focused on applying coherence, spectral decomposition, structure-oriented filtering, and volumetric curvature to mapping fractures and karst with a particular focus on resource plays.