Multi-Spectral Coherence

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**ABSTRACT**

Seismic coherence is routinely used to delineate geologic features that might otherwise be overlooked on conventional seismic amplitude volumes. In general, one wishes to interpret the most broadband data possible. However, because of the thickness tuning effects, certain spectral components often better illuminate a given feature with higher signal-to-noise ratio than others. Clear images of channels and other stratigraphic features that may be buried in the broad-band data may “light up” at certain spectral components. For the same, coherence attributes computed from spectral voice components (equivalent to a filter bank) also often provide sharper images, with the “best” component being a function of tuning thickness and reflector alignment across faults. While one can co-render three coherence images using RGB blending, display of the information contained in more than three volumes in a single image is difficult. We address this problem by summing a suite of structure-oriented covariance matrices computed from spectral voices resulting in a “multi-spectral” coherence algorithm.

We demonstrate the value of multi-spectral coherence by comparing it to both RGB blended volumes and coherence computed from spectrally balanced, broad-band seismic amplitude volume from a .megamerge survey acquired over the Red Fork Formation of the Anadarko Basin, Oklahoma. The multi-spectral coherence images provide better images of channel incisement and are less noisy than those computed from the broadband data. Multi-spectral coherence also provides several advantages over RGB blended volumes: first, one can combine the information content from more than three spectral voices; second, only one volume needs to be loaded into the workstation; and
third, the resulting gray-scale images can be co-rendered with other attributes of interest, for example, petrophysics parameters, plotted against a polychromatic color bar.
INTRODUCTION

Twenty years after its inception in the mid-1990s, seismic coherence volumes are routinely used to delineate structural and stratigraphic discontinuities such as channels, faults and fractures, to highlight incoherent zones such as karst collapse and mass transport complexes, and to identify subtle tectonic and sedimentary features that might otherwise be overlooked on conventional amplitude volumes (Ogiesoba and Hart, 2009; Sun et al., 2010; Li et al., 2015; Qi et al., 2017). Estimates of seismic coherence (Bahorich and Farmer, 1995; Marfurt et al., 1998; Gersztenkorn and Marfurt, 1999; Lu et al., 2005; Wu, 2017; Yan et al., 2017) that highlight changes in seismic waveform or amplitude across a discontinuity provide a quantitative measures of the geological discontinuity.

In general, the quality of a coherence image is a direct function of the quality of the seismic amplitude from which it is computed. For this reason, the most important step in coherence computation is to ensure that the processed data exhibit high bandwidth, are accurately imaged, and are free of multiples and other types of coherent noise. Once in the interpreter’s hands, many seismic amplitude volumes benefit from subsequent post-stack structure-oriented filtering and spectral balancing (Chopra and Marfurt, 2007).

The broad-band seismic response of a given geological feature is composed of its response of its constituent spectral bands. However, such boundaries and edges computed from broad band seismic data does not give a measure of the vertical scale of the discontinuity. Through constructive and destructive interference, the resulting vertical and horizon slices often represent the response of the strongest, or dominant frequency corresponding to structure and stratigraphy of given time tuning thickness in the analysis window.
Spectral decomposition methods transform a 1D seismic amplitude trace into 2D time-frequency spectral magnitude and phase components (Partyka et al., 1999). Certain spectral components will exhibit a higher signal-to-noise ratio than others. In addition, thin beds that are tuned might be expected to better exhibit discontinuities at their higher amplitude tuning frequency than at other frequencies (Peyton et al., 1998). For the same reason, spectral attributes of relatively narrow band components often delineate anomalous geological features that are otherwise buried within the broadband seismic response.

Not all spectral components contain signal, while others may be overly contaminated by noise. For example, Fahmy et al. (2005) recognized that a deep reservoir tuned at 11 Hz was masked by strong, higher-frequency multiples. By simply removing this high frequency components they could obtain a clear image of the reservoir and perform an accurate AVO analysis. Gao (2013) noticed that subtler structural details in reservoirs are revealed using a higher frequency wavelet as the spectral probe. Abele and Roden (2005) found that curvature computed at certain spectral components better correlated to microseismic events than others. Sun et al. (2010) used discrete frequency coherence cubes in fracture detection and found that high frequency components can provide greater detail.

Recently, Li and Lu (2014) showed that coherence computed from different spectral components can be combined to provide a qualitative measure of the scale of geological discontinuities such as faults, channels, caves, and collapse features. We propose a multi-spectral coherence method to map variations of thickness and edges to
map the different stage fills of incised valley system. We use RGB color blending technique to integrate attributes computed at different spectral components. The data volume is part of mega-merge survey from CGGVeritas over the Anadarko Basin, Oklahoma, and incorporates a survey which was one of the first applications of spectral decomposition interpreted by Peyton et al. (1998) using 36 Hz spectral component and full band coherence. While our analysis of mega-merge survey corresponds well with the original incised valley interpretation, the improved data quality due to surface consistent deconvolution and statics as well as the larger migration aperture results in much sharper channel images.

**METHODOLOGY**

**The Covariance Matrix and Energy Ratio Coherence**

Gersztenkorn and Marfurt (1999) describe the first implementation of coherence based on the eigenvectors of the covariance matrix. Since that time, several details have been modified, including computing the covariance matrix, C, from the analytic trace, composed of the original data, d, and its Hilbert transform, dH along structural dip:

$$C_{mn} = \sum_{k=-K}^{K} \left[ d(t_{k}, x_{m}, y_{m})d(t_{k}, x_{n}, y_{n}) + d^{H}(t_{k}, x_{m}, y_{m})d^{H}(t_{k}, x_{n}, y_{n}) \right],$$

(1)

where $t_{k}$ is the time of a structurally interpolated sample at a distance $(x_{m}, y_{m})$ about the analysis point at $(x=0, y=0, t=0)$. Computing the eigenvectors of C provides a means of computing a Karhunen-Loève filtered version of the data, $d_{KL}$ and $d^{H}_{KL}$. If the data d have been previously spectrally balanced, the broadband energy ratio coherence (Chopra and Marfurt, 2007), $s_{bb}$, can then be defined as
Filter Banks and Spectral Decomposition

Hardage (2009) recognized that because of the variable signal-to-noise ratio at different frequencies, faults were more easily identified in his data on the low frequency components that were less contaminated by strong interbed multiples. The continuous wavelet transform can be viewed as the application of a suite of filter banks to the original seismic data. Li and Lu (2014) and Honorio et al. (2016) computed coherence from a suite of spectral components and combined them using RGB color blending, resulting in not only improved discontinuity images, but in addition an estimate at which spectral bands the discontinuities occurred. The main limitation of this approach is that only three spectral components can be co-rendered at any one time.

To address this limitation, Dewett and Henza (2015) combined multiple coherence attributes images using self-organizing maps. Each energy-ratio coherence volume was computed along structure from spectral voices, $u(f)$:

$$u(f_i, t_k, x_m, y_m) = a(f_i, t_k, x_m, y_m) \exp[i\phi(f_i, t_k, x_m, y_m)], \quad (3)$$

which is constructed using a spectral decomposition algorithm, where $a$ is the spectral magnitude and $\phi$ the spectral phase of each component.

Sui et al. (2015) also noted the value of multispectral coherence and 3-component limitations of RGB display, and computed coherence based on spectral magnitudes, $a(f_i, t_k, x_m, y_m)$, using the covariance matrix

$$C_{mn} = \sum_{i=1}^{L} \sum_{k=-K}^{K} [a(t_k, f_i, x_m, y_m) a(t_k, f_i, x_n, y_n)]. \quad (4)$$
By not using the phase component, the covariance matrix is less sensitive to dip, allowing the use of a simpler, non-structure-oriented computation.

We build on the above work but rather than use the spectral magnitude computed along time slices used in Equation (4), we use the spectral voices and their Hilbert transforms computed along structure described by Equation (3) to obtain the covariance matrix (Marfurt, 2017):

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

(5)

We will then compute coherence from the original broad-band data, from each spectral voice component, and compare them to the multispectral coherence computed using Equation (5).

DATA DESCRIPTION

The study area is located in the eastern part of Anadarko Basin, Oklahoma (Figure 1). Pennsylvanian rocks throughout most of the Anadarko Basin are dominated by shallow shelf marine clastics. The target is the Red Fork sand of Middle Pennsylvanian age which lies at an approximate depth of 2700 m (~9000 ft) and is composed of clastic facies deposited in deep-marine (shale/silt) to shallow water fluvial-dominated environment. The Red Fork sand is sandwiched between limestone layers, with the Pink Lime on top and the Inola Lime on the bottom. The Oswego Lime that lies above the Pink Lime and the Novi Lime that lies below the Inola Lime, are very prominent reflectors that can be readily mapped on the seismic amplitude data, providing an approximation to a fixed geologic time. The Upper Red Fork incised valley system consists of multiple stages
of incision and fill, resulting in a stratigraphically complex internal architecture (del Moro et al., 2013).

The survey of interest was shot at various times, beginning in the mid-1990s. CGGVeritas acquired licenses for these surveys, shot infill data in 2009 where necessary, and carefully reprocessed them, resulting in a megamerger survey. In addition to more modern statics and deconvolution algorithms, the most significant advantage of the megamerger survey is the inclusion of a wider migration aperture, providing the diffraction energy needed to image faults and stratigraphic edges (Del Moro et al., 2013; Li et al., 2015). The incised valleys are characterized by discontinuous reflections of varying amplitude which are difficult to interpret laterally (Peyton et al., 1998). It is difficult to interpret the Red Fork incised valley using traditional interpretation techniques (auto picking horizons, amplitude mapping, etc.). Individual stages of fill are almost impossible to identify.

**ATTRIBUTE EXPRESSION ON VALLEY FILL**

Figure 2 displays Red Fork stratal slices through the seismic amplitude and coherence volumes. Vertical slices through the seismic amplitude provide an indication of erosion, but do not allow one to identify the various stages of valley fill. The coherence attribute in Figure 2b was computed volumetrically from the broad band seismic data after spectral balancing using a 5-trace, 11-sample (±20 ms), and as expected, image the boundaries of the valley as well as some internal incisements; however, the overall internal detail is diffuse. The main reason of this lack of detail is that coherence was computed from the broad band seismic amplitude data volume, and thus measures a mix of valley fill stages in the same image. In contrast, lateral changes in sedimentary layers
and channel incisement of a given thickness are often better imaged near their tuning thickness.

The Red Fork incised valley can be mapped using spectral components between about 20 Hz and 50 Hz. Peyton et al. (1998) chose 36-Hz amplitude slice as the best images of the valley throughout the survey area resulting in the image shown in Figure 3. Their coherence example, represents channel features illuminated by the dominant frequency components.

The cartoon by Laughlin et al. (2002) in Figure 4 shows how thicker and thinner stratigraphic features will be tuned in at correspondingly lower or higher frequency components. In practice, the interpreter animates through a suite of spectral components and stops the animation when a particular feature of interest is well delineated. The same strategy should be also adopted in valley fill analysis. Figure 5 shows the dominant frequency map of Red Fork formation. Different types of geological structures and different stages of valley fill each with its own tuning thicknesses give rise to anomalies at different dominant frequencies.

MULTISPECTRAL ANALYSIS

Spectral magnitude and coherence corresponding to these tuned frequencies provide clearer images. Though spectral decomposition reveals more details, it generates a series of maps or volumes at different frequencies, which are analyzed one by one or through animation. Blending RGB (red-green-blue) images have long been used to express multiple spectral components in a single image (Balch, 1971). A more recent exposition on the value of RGB in rendering multiple spectral images of channels can be
found in Leppard et al. (2010). We use RGB color blending technique in Figure 6 to display the 20, 35 and 50 Hz spectral components. As shown in the RGB color map, if the energies in all three colored channels are at or above the threshold amplitude, the blended color is white, while if the energy of one channel is stronger than the other two, its color would dominate. The new information is revealed by the color changes. The 20 Hz component is plotted against red and better delineates Stages II, III and V. The 35 Hz component is plotted against green and delineates medium thickness Stage V channels. The 50 Hz component is plotted against blue and delineates thinner Stage V channels and part of Stage III. Compared with the interpretation in Figure 3, which is a part of our survey, note that the stages interpreted by Peyton et al. (1998) also display in different colors. Though Stage I is not clearly separated from Stage II or III, which cannot be achieved neither on single frequency slice interpretation as Peyton et al. (1998) did, other stages as well as some geological structures in other parts of the survey are displayed with different temporal tuning thickness. There are other good methods that can analyze tuning thickness variance, but none are as easy to create or as routinely used.

We selected 20, 35 and 50 Hz to compare to Peyton et al.’s (1998) 36 Hz component image in Figure 1.3. Next, in Figure 7 we compute coherence from each of these spectral components, providing a measure of the edges sensitive to the relative thicknesses of the different stages of valley fill. Color blending of coherence is slightly different than color blending of spectral magnitudes, where the result is subtractive rather than additive. If all spectral magnitudes are zero, one obtains a black image. If all spectral coherences are unity, one obtains a white image. A high spectral magnitude at the 20 Hz component results in a red anomaly. In contrast, a low spectral coherence at 20 Hz results
in less red, or a cyan anomaly. The black (dark gray) lines are the channel boundaries which appear on all the selected frequency components. The boundaries of relative thick channels showing on lower frequency component painted red would appear as cyan after blending (the opposite color of red on the color wheel), while edges of thinner channels in part of Stage III and V appear magenta or yellow. Since the channel edges can be characterized by other frequency bands, the channel edges shown in Figure 7 are not as many as those in Figure 2b. In addition, for the most area of the image without channel boundaries, the color delegates the change of coherent energy, for example, the large magenta (which is the opposite of green) area implies that lower coherent energy in middle frequency component. Figure 8 adds a fourth broadband coherence image shown in Figure 2b using opacity to the RGB blended map shown in Figure 7. Comparing Figures 7 and 8 shows the advantage brought by spectral component coherences. Through the colorful attribute integration image, one is no-longer thickness unaware.

Until now, the coherence images have been directly computed from different spectral voice components. However, thin beds that are tuned might be expected to better exhibit discontinuities at their higher amplitude tuning frequency than at other frequencies. For this reason, one may wish to not only examine coherence computed from different voices, but somehow combine them into a single composite image.

Figure 9 shows coherence computed from six spectral voices (equivalent to six band-pass filtered data volumes) beginning with corner frequencies of 10-15-25-30 Hz and ending with 110-115-125-130 Hz. As discussed above, different spectral bands highlight different geological features. Note that in Figures 9e and 9f that the noise becomes equal to, and then even stronger than signal.
Figure 10b shows the multispectral coherence computed from all seven filter bank voices defined by the covariance matrix in equation 5. Compared with the broadband coherence shown in Figure 10a, random noise (indicated by red dashed ellipses) has been suppressed and the channel boundaries sharper at some locations.

While the computational effort of multispectral coherence increases linearly with the number of spectral components analyzed, the actual increase is somewhat less because of fixed i/o and data transfer overhead. Most of this cost is in computing the individual covariance matrices defined by equation 5. In our implementation, we allow the computation of the individual components as well, providing the images shown in Figure 7. While we find the multispectral coherence image to be “better” than the bandlimited and broadband coherence images, co-rendering the individual images (Figure 11) still provides additional insight. Analysis of such images provide insight into which spectral component is a meaningful indicator of a given structural or stratigraphic feature.

Thus, by more fully using the spectral components, the corresponding coherence map and multi-spectral coherence attribute, the stage identification and valley fill boundary delineation can be more completely interpreted.

**CONCLUSIONS**

The interpretation of incised valley fill can be difficult on conventional amplitude volumes. Multispectral coherence provides improved images over traditional coherence images, even if the seismic amplitude data have been previously spectrally balanced. While much of this improvement can also be found in RGB blended volumes, multispectral coherence provides several advantages: (1) one can combine the
information content of more than three coherence volumes, (2) there is only one rather than three volumes to be loaded into the workstation, which may be a limitation for very large data sets, and (3) the grey-scale image can be co-rendered with other attributes of interest plotted against a polychromatic color bar, such as P-impedance vs. Poisson’s ratio or SOM cluster results. Although the computation cost increases with the number of spectral voices, the added time savings in interpreting ambiguous channels and the revelation of previously hidden features is of significant value to the human interpreter.
REFERENCES


Hardage, B., 2009, Frequencies are fault finding factors; looking low aids data interpretation: AAPG Explorer, 30, no. 9, 34.


Figure 1. Location map of Anadarko basin area on map of Oklahoma, and the study survey is located inside the study area marked by red boundary (after del Moro et al., 2013).
Figure 2. Stratal slices through (a) seismic amplitude and (b) coherence volumes along the top Red Fork Formation from a mega-merge survey. Note the edges of the incised valley are shown on the coherence slice. Data courtesy of CGG-Veritas.
Figure 3. Peyton et al.’s (1998) original slice with interpretation through the 36-Hz spectral magnitude computed from the original 1995 seismic data volume. This same data volume formed part of the mega-merge survey shown in Figure 2.

Figure 4. A cartoon of thin bed tuning. In thin reservoirs with varying thickness (left) seismic data with higher dominant frequency would highlight the thinner parts of the reservoir on amplitude maps (middle), while seismic with a lower dominant frequency would highlight the thicker parts on an amplitude map (right). (after Laughlin et al., 2002)
Figure 5. Dominant (or peak) spectral frequency image of the Red Fork horizon, which shows that the target horizon has different tuning thickness. The magnitude of the spectral component is plotted against a gray scale, thereby modulating the image.

Figure 6. RGB blended spectral magnitude components at 20 Hz (in red), 35 Hz (in green) and 50 Hz (in blue).
**Figure 7.** RGB blended image of coherence corresponding to Figure 6 computed from the 20 Hz (in red), 35 Hz (in green) and 50 Hz (in blue) spectral components.

**Figure 8.** The same image shown in Figure 7 but now co-rendered with that of Figure 2b. Edges that are not overprinted in black were delineated by coherence computed from the corresponding spectral components, but not by the broad band coherence computation.
Figure 9. Coherence attributes calculated from different spectral bands (a) 10-15-25-30 Hz, (b) 30-35-45-50 Hz, (c) 50-55-65-70 Hz, (d) 70-75-85-90 Hz, (e) 90-95-105-110 Hz, (f) 110-115-125-130 Hz. Note that different spectral bands highlight different features, and the high frequencies include noises.
Figure 10. (a) The same horizon slice along the top Red Fork Formation shown in Figure 2 through broadband coherence, and (b) through multispectral coherence computed using all six spectral bands. Yellow arrows indicate channel boundaries are poorly delineated on the broadband coherence image. Red dashed ellipses indicate noisy areas that have been suppressed.
Figure 11. Co-rendered coherence for three of the six spectral bands. Red: 10-15-25-30 Hz, Green: 30-35-45-50 Hz, Blue: 50-55-65-70 Hz.