Wavelet transform Teager-Kaiser energy applied to a carbonate field in Brazil

Marcílio Castro de Matos and Kurt J. Marfurt, University of Oklahoma
Paulo Roberto Schroeder Johann, João Adolfo Rosseto, Augusto Tortolero Araujo Lourenço, and Josiane Luzia Diniz, Petrobras

Spectral decomposition has proven a powerful means to identify strong amplitude anomalies at specific frequencies that are otherwise buried in the broadband response. Partyka et al. (1999) showed that the seismic spectrum response from a short time window depends on the acoustic properties and thickness of the layers spanned by the window. They applied this idea to good quality marine data to delineate thin channels in Tertiary sediments in the Gulf of Mexico. They also applied spectral decomposition to moderate quality land data to delineate incised channels in Paleozoic rocks in the U.S. midcontinent. Since then, spectral decomposition has been applied to reservoir characterization, hydrocarbon detection, and stratigraphic analysis.

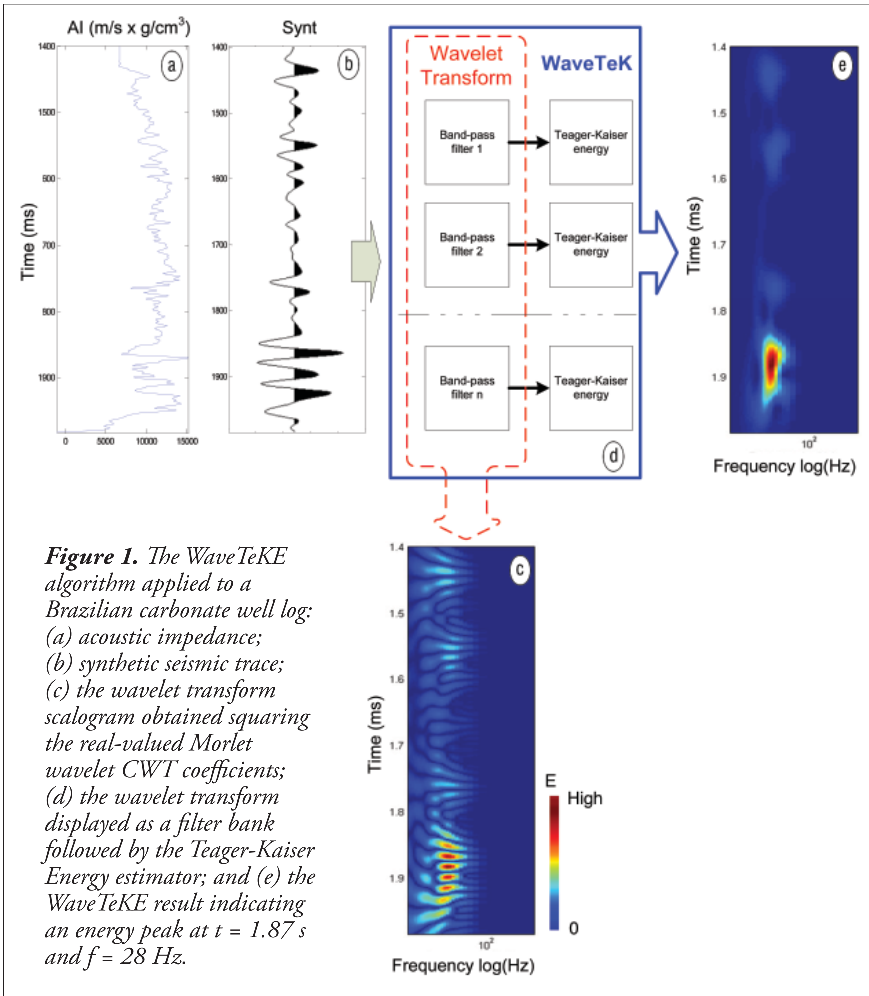


Figure 1. The WaveTeKE algorithm applied to a Brazilian carbonate well log: (a) acoustic impedance; (b) synthetic seismic trace; (c) the wavelet transform scalogram obtained squaring the real-valued Morlet wavelet CWT coefficients; (d) the wavelet transform displayed as a filter bank followed by the Teager-Kaiser Energy estimator; and (e) the WaveTeKE result indicating an energy peak at t = 1.87 s and f = 28 Hz.

Spectral decomposition has mainly been applied to clastic depositional systems, where fluvial deltaic channels, deepwater turbidites, and mass transport complexes cut through an otherwise homogenous matrix. Since carbonates are often grown in place rather than transported to their depositional site and therefore suffer significantly greater diagenetic alteration, intracarbonate impedance changes are subtle and may not have an easily identified spatial pattern. For this reason, spectral decomposition applied to carbonate reservoirs is still challenging, and the relation between carbonate rock properties and seismic spectral content is not very well developed. Nevertheless, Masafero et al. (2004) show that variation in facies and diagenesis plays strongly affect both bulk density and sonic velocity and, thus, acoustic impedance in carbonate systems. Skirius et al. (1999) and Chopra and Marfurt (2007) show how the shape or geomorphology of reflection patterns, coupled with appropriate models of deposition and diagenesis, aid in mapping carbonate reefs and karst. Pearson and Hart (2004) use spectral components to predict the porosity of a carbonate reservoir by estimating the slope from peak to maximum spectral frequency, coupled with the ratio of the number of positive samples over the number of negative samples within a time interval. Based on this previous work, we anticipated that spectral decomposition could reveal important features in our Brazilian carbonate reservoir.

The energy associated with the motion of a medium as a wave passes through it is one of the most important characteristics of a wave. Usually, we are not concerned with the total energy of a wave but rather with the energy per unit volume, or the energy density in the vicinity of the reflection point. The most common way to estimate the energy of a signal is to simply square its amplitude samples and then form a running-window sum, thereby generating average energy, rms amplitude (by taking the square root of the energy or L2 norm measure of amplitude), or average absolute amplitude (the L1 norm measure of amplitude) maps. A slightly more sophisticated means to compute the energy is by calculating the envelope of the complex trace. Often called the "instantaneous" envelope or the reflection strength, this measure is based on the Hilbert transform, and thus is also a weighted (1/t) average of the amplitude of adjacent samples. Kaiser (1990) introduced a much more local nonlinear energy estimate valid for monofrequency signals that takes into account the narrower neighborhood of each time sample. This algorithm has since been called Teager-Kaiser (or TK) energy.

De Matos and Johann (2007) modified Kaiser's algorithm and applied it to continuous-wavelet-transform components of the seismic data rather than to the broadband seismic data themselves. They showed that the TK energy is directly proportional to the energy of the seismic wavefield. They applied this workflow to a clastic reservoir and used the resulting time-frequency representation to detect and track anomalously strong seismic events that were otherwise buried in the broad spectral response.

In this paper, we review their workflow and apply the CWT associated with the TK energy to seismic data acquired over a carbonate reservoir in Brazil.

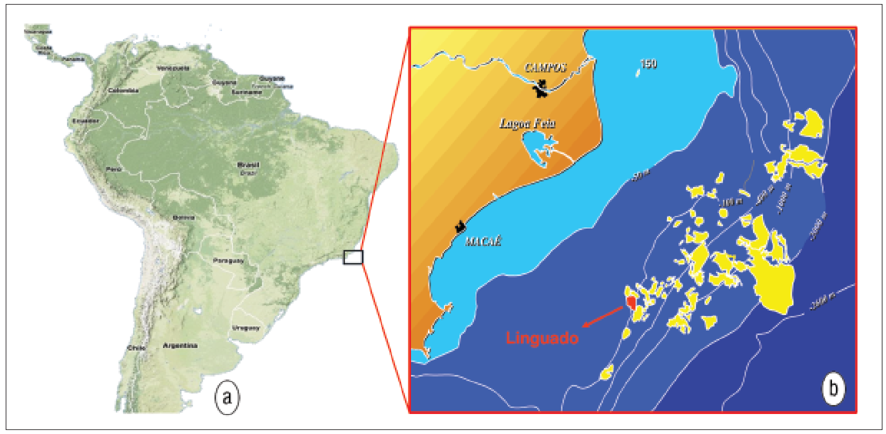


Figure 2. Location of (a) Campos Basin and (b) Linguado Field.

The wavelet transform Teager-Kaiser energy

It is well known that the seismic energy density, E, for a monofrequency signal can be expressed as

$$E = \frac{1}{2}\rho\omega^2 A^2 = 2\pi^2\rho f^2 A^2 \qquad (1)$$

and is proportional to the density of the medium, ρ, the square of the frequency, ω (in radians/s) or f (in Hz), and the square of the amplitude, A, of the wave (Sheriff and Geldart, 1995).

Using an analog mass-spring physical model, Kaiser proved that the energy of a discrete time signal at time $t = n\Delta t$ can be expressed as:

$$E_n = \frac{1}{2} m\omega^2 A_n^2 \cong x_n^2 - x_{n+1}x_{n-1} \qquad (2)$$

where $E_n = E(n\Delta t)$, m is the mass of the object suspended by a spring, A is the amplitude of the oscillation, and x_n are the samples of the discrete time signal. If we consider the discrete mass, m, in Equation 2 to be a lumped approximation of the continuous density, ρ, in Equation 1, we note that these two equations are identical so that we can use Equation 2 to estimate the instantaneous TK energy of the seismic wavefield. Hamila et al. (1999) called the TK energy a nonlinear energy-tracking signal operator and proved that, for analytic signals, it can be obtained by summing the TK energy of the real and imaginary parts.

Since Equation 2 is strictly true for a monofrequency wavefield, Kaiser suggested band-pass filtering the data before calculating the TK energy. We therefore follow Mallat (1999) who showed that the wavelet transform can be implemented through special band-pass filter banks, resulting in a joint time-frequency representation of the seismic wavefield. However, the continuous wavelet transform (CWT) is more than a simple bank filter. Rather, the CWT has multiresolution

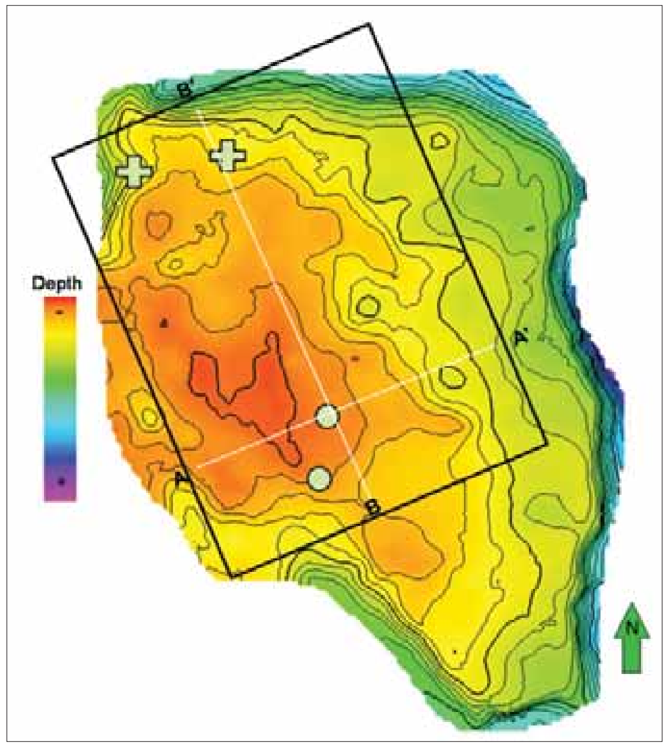


Figure 3. Depth structure map of the top of the reservoir (Outeiro Member). Circles denote producer wells. Crosses denote dry holes. The rectangle indicates the studied area.

properties, having high spectral resolution for low-frequency events and high temporal resolution for high-frequency events. Since seismic signals are usually sampled at 2 ms, corresponding to a 250-Hz Nyquist frequency, and have a dominant frequency between 30 and 50 Hz, CWT is a very good tool to detect low-frequency events with high spectral resolution and at the same time detect high-frequency events with high temporal resolution.

Figure 1 illustrates how the wavelet transform TK energy (WaveTeKE) algorithm works. Figure 1a shows the acoustic impedance measured in an oil well in a carbonate reservoir in Linguado Field in Brazil's Campos Basin. Figure 1b shows the corresponding synthetic seismogram, obtained by convolving the reflectivity with the Ricker wavelet. Figure 1c shows the

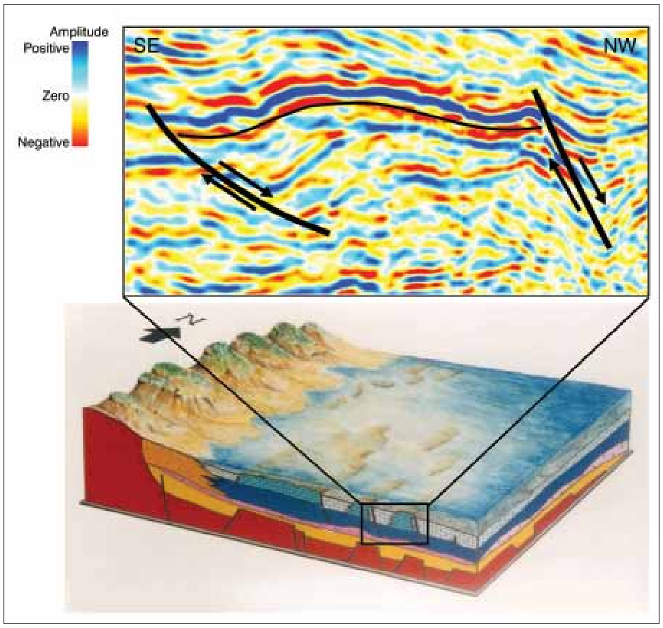


Figure 4. Block diagram of the Albian-age carbonate platform (bottom). Note the rollover structures on the seismic line (top). Also note the change in vertical resolution below the top carbonate pick (yellow) in the time-migrated seismic data. Such loss of high frequency commonly indicates a rugose top of carbonate.

time-frequency amplitude, A(f,t), and Figure 1d shows the time-frequency TK energy, E(f,t). Note the strong event at t = 1.9 s in Figure 1e that corresponds to the carbonate reservoir oil field.

Application to a carbonate field in Campos Basin

Linguado Field (Figure 2) is 80 km from the coast of the State of Rio de Janeiro, in the southern part of Campos Basin, in water depths ranging from 95 to 110 m. The carbonate reservoir is of middle-to-lower Albian age (110–105 Ma) and belongs to Quissama Formation of the Macae Group.

Structurally, the reservoir is a rollover anticline associated with deeper salt tectonics and listric faulting (Figures 3 and 4a). The reservoir is represented by an elongated geometry with smooth dips with the oil column thickest (125 m) over the structural apex with an oil-water contact in all four directions. Based on cores, the sedimentary facies have been defined by textural differences. The best reservoir facies have a porosity of about 27% and permeability greater than 1000 mD, and they are primarily constituted by oolitic and oncolite calcarenites (Guardado et al., 1989). Secondarily, calcirudites, peloidal calcarenites, and rarely bioclastics and algal detritus compose intermediate-quality facies. Figure 4 illustrates the carbonate platform along the Albian depicting the rollover structures along with a representative seismic line showing the structural style.

Given that seismic trace spectrum decomposition is a measure of stratigraphic variability, we applied the algorithm to the 3D survey acquired over Linguado Field. The rectangular area in Figure 3 indicates the studied area. The two circles represent producer oil wells and the two crosses represent dry holes. Figures 5a and 5b show two vertical slices close to the wells through the original amplitude volume.

Like all joint time-frequency spectral decomposition algorithms, WaveTeKE applied to three-dimensional data generates four-dimensional data, with one 3D volume generated for each decomposed frequency. Interpretation involves analyzing constant frequency cubes, by examining frequency "gathers" or by computing statistically significant measures of the full spectrum.

Previous work by de Matos et al. (2005) and Liu and Marfurt (2007) showed how the maximum (or "peak") spectral frequency and its associated

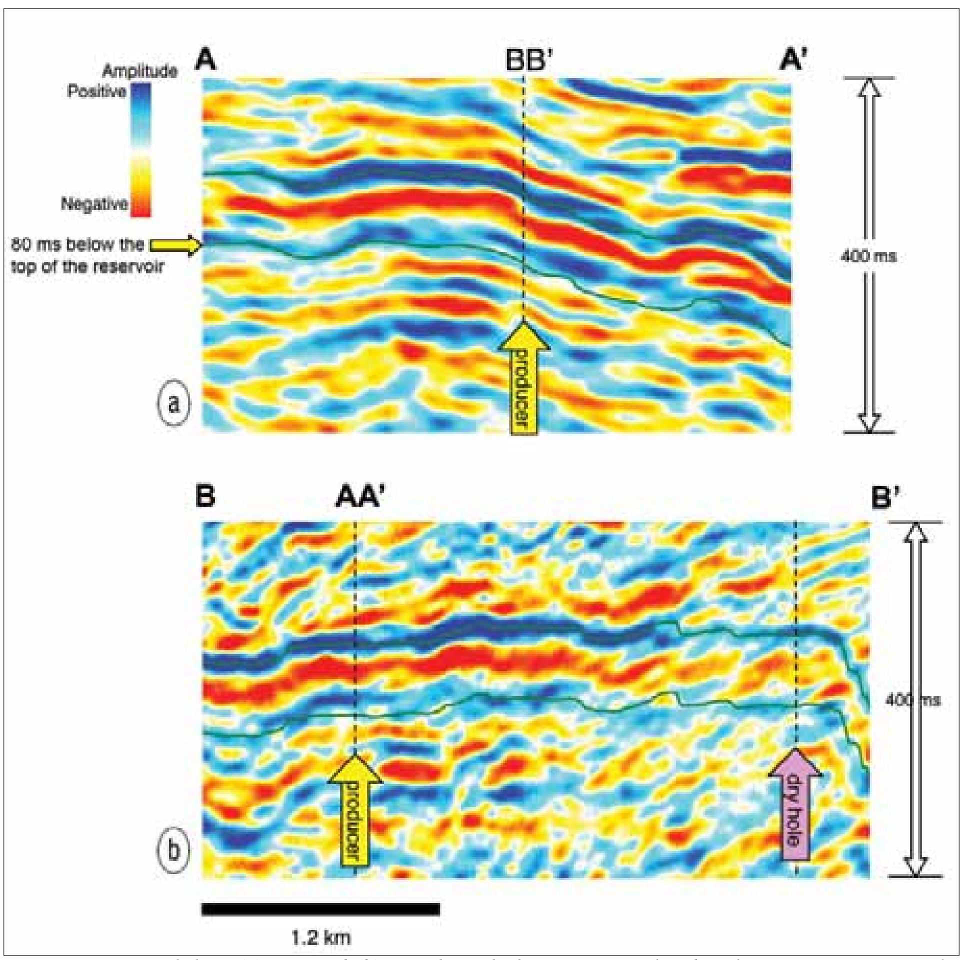


Figure 5. Vertical slices (a) AA' and (b) BB' through the seismic amplitude volume. Upper green pick denotes the top of the carbonate reservoir.

amplitude is a statistical measure that can be directly related to important geologic features. Following them, we extract the global peak energy using the WaveTeKE algorithm given by Equation 2 for the whole 3D volume. Figure 6 shows schematically how the global peak frequency and other frequency attributes are obtained from the joint time-frequency distribution to each time trace sample. Figures 7b and 7c display the global peak energy; Figure 7a displays a formation attribute obtained by picking the most positive global peak energy with a window extending 80 ms below the top of the reservoir. We note that the reservoir area is well delineated. As a reference, in both Figures 7b and 7c the upper yellow picks represent the top of the reservoir, and the vertical black dashed lines represent the wells. These lines confirm the value of the proposed algorithm—in these data, producer wells correlate to high-energy frequency reflectors while nonproducers relate to low-energy reflections.

Figure 8 shows the 80-ms time interval

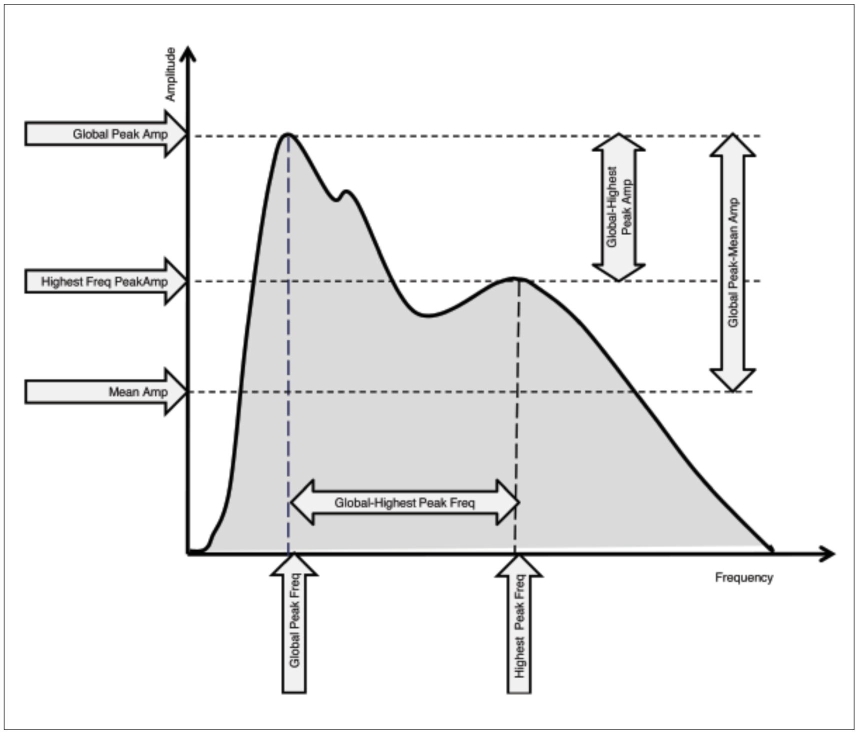
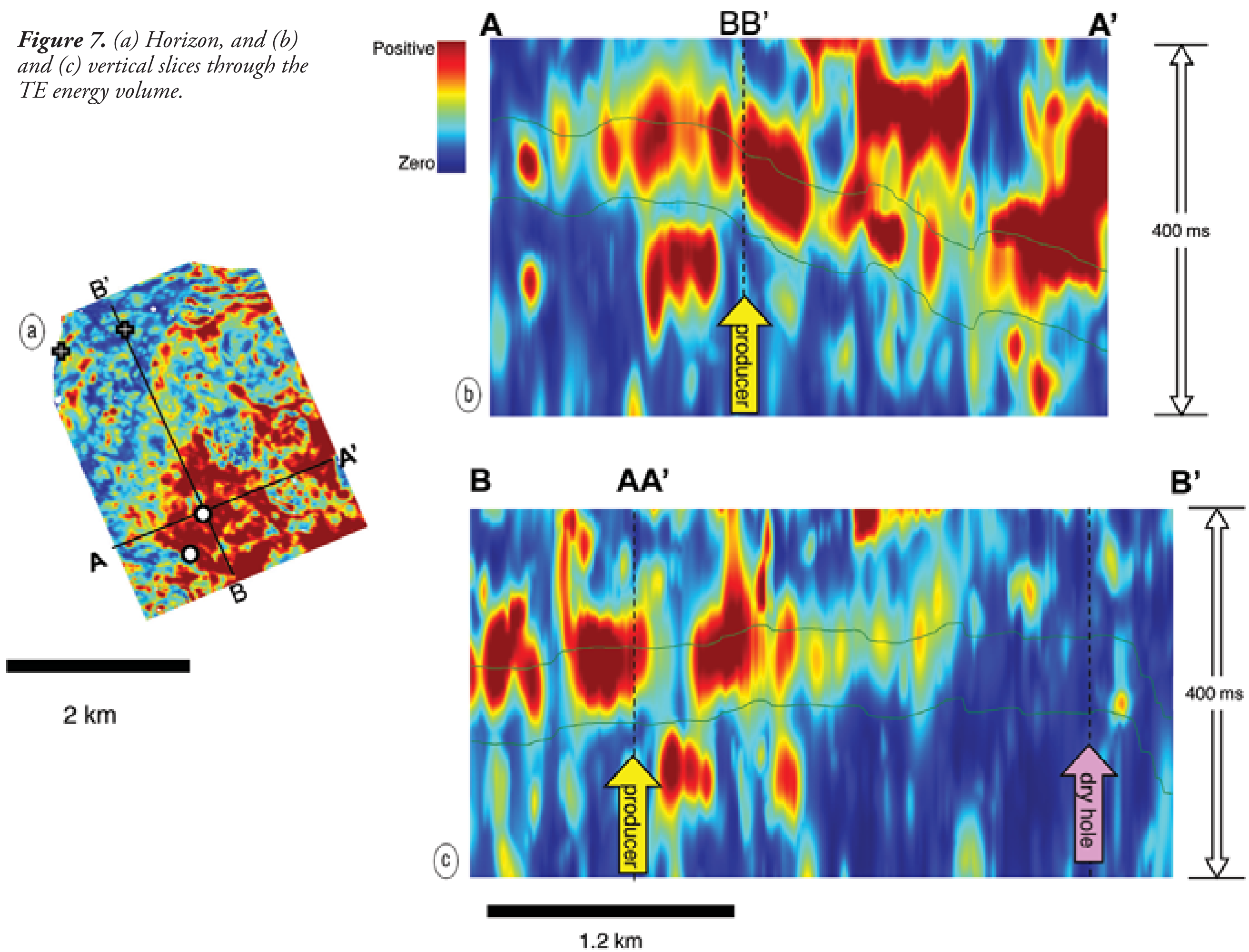


Figure 6. *Frequency attributes obtained from the joint time frequency distribution to each time trace sample.*

Figure 7. *(a) Horizon, and (b) and (c) vertical slices through the TE energy volume.*



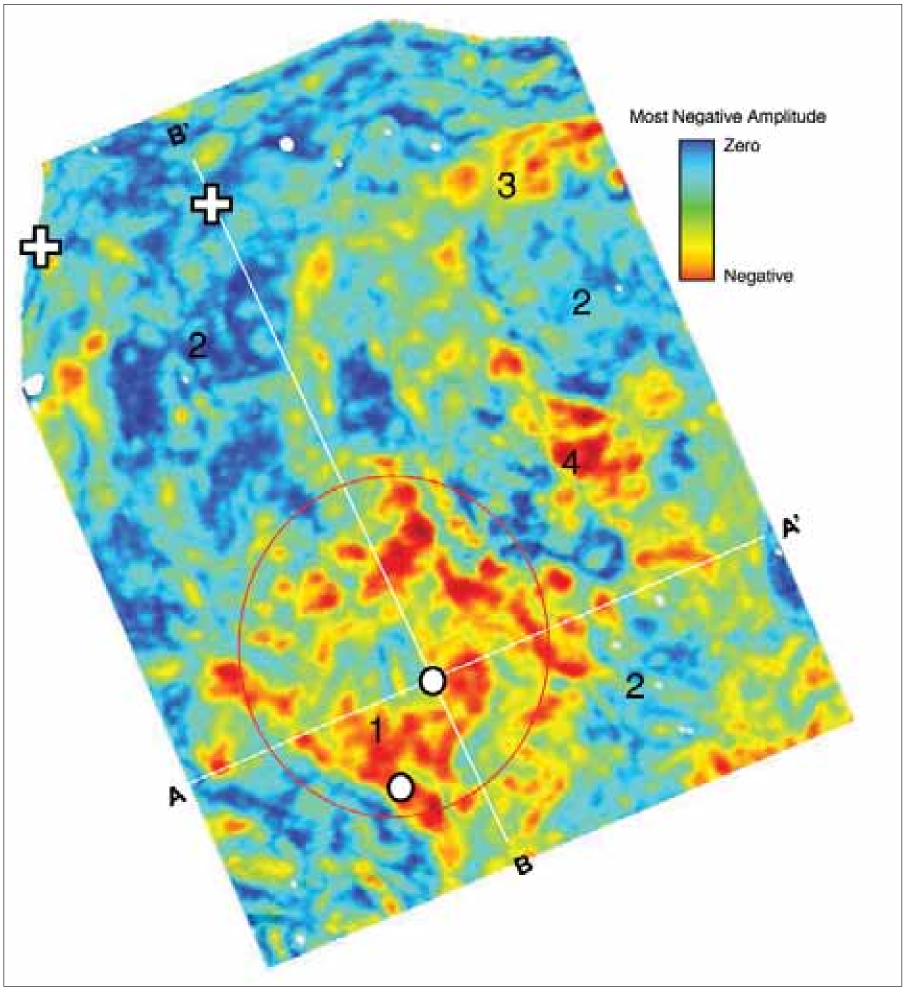


Figure 8. *80-ms time interval for the seismic attribute strongest negative amplitude. Circles represent producers, and crosses represent dry holes. The negative amplitude dims close to the dry well, and the strongest negative amplitudes are associated with paleo high-carbonate areas. This seismic attribute has proven a good indicator of reservoir quality for this particular field.*

attribute that displays the minimum amplitude (strongest negative value) below the reservoir top. We note in Figure 5b that this amplitude dims close to the dry well; this seismic attribute has proven a good indicator of reservoir quality for this particular field.

Radovich and Oliveros (1998) and Guo et al. (2008) showed that the HLS color model is an effective way to combine two different attributes by modulating a primary attribute such as global peak frequency plotted against hue by a secondary attribute such as global peak amplitude plotted against lightness. Figure 9 shows the time-interval peak WaveTeKE maximum global peak frequency and its associated global peak amplitude plotted together using such a 2D hue-lightness color bar. Observe that known paleo high areas where high energy, high permeability, and porosity carbonates were developed (which were also not affected by diagenesis) are clearly related to high WaveTeKE peak energy. We note intermediate values of about 30 Hz for the peak frequencies, similar to the frequency of the synthetic seismic trace shown in Figure 1. In this region, labelled as 1 in Figure 9, thick-layered grainstones facies predominate. High peak frequencies with moderate energy showed in region 2 are associated in this field to carbonates developed with low energy, packstones and wackstones, with a lesser amount of thin grainstones. In Figure 9 region 3, high WaveTeKE peak energy with moderate peak frequencies can be associated to some secondary bio-constructions, while in region 4 a local paleo high with high-energy facies can also be associated to high peak energy with intermediate peak frequencies.

Using this stratigraphic interpretation, the results help us to interpolate and extend important carbonate field features seen in the wells. Comparing Figures 8 and 9, we observe in region 1 more continuity associated with the high-energy carbonate reservoirs, exactly as confirmed by the production data in this area. We also observe that discontinuities associated with faults in region 3 are better imaged. Therefore, WaveTeKE provides significantly better delineation than the strongest negative amplitude time-interval seismic attribute (shown in Figure 8) previously used to delineate the reservoir.

Conclusions

We show that the Teager-Kaiser energy can be computed for real seismic data through the joint time-frequency representation and that it is directly related to the seismic energy density. TK energy appears quite effective in delineating strong amplitude, high-frequency events associated with producing areas of a carbonate reservoir. The results we obtained show WaveTeKE's potential use as a reservoir delineation tool to detect energy associated with important geological facies measured in wells. Other joint time-frequency decomposition such as matching pursuit can also be used to compute the spectral components.

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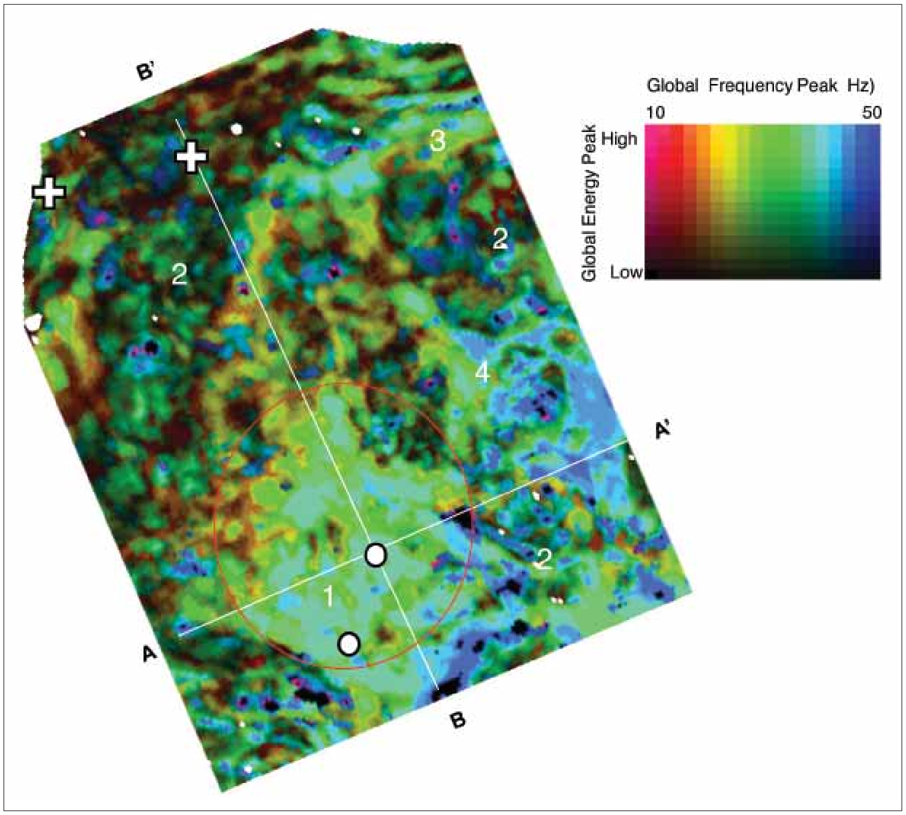

Figure 9. *Dual-attribute color display of energy versus frequency of the global peak of the E(f,t) spectra given by Equation 2. Circles represent producers, and crosses represent dry holes. Well control indicates that 1 = known paleo high areas where high energy, high permeability, and porosity carbonates were developed with predominant thick-layered grainstones facies; 2 = carbonates developed with low energy, packstones and wackstones, with a lesser amount of thin grainstones; 3 = some secondary bio-constructions; and 4 = a local paleo high with high-energy facies.*

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Corresponding author: marcilio@matos.engr.br