4D Seismic Spectral Decomposition over a Pre-Salt Carbonate Reservoir: a feasibility study

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Summary

In this paper, we investigate the use of spectral decomposition and facies classification on time-lapse data related to a Brazilian pre-salt carbonate reservoir. Synthetic seismic data were generated through petro-elastic modeling (PEM), which is based on a representative geological model and flow simulator dynamic properties. Reservoir pressure and saturation distributions are used that corresponds to periods of time, in which, real time-lapse seismic data will be available. The spectral decomposition method used, is based on a modified matching pursuit algorithm. At this stage, we focus on the interpretation of the spectral decomposition, mainly on geometric effects. We conclude that the use of spectral decomposition on 4D seismic data enhances reservoir heterogeneities and correlates with water saturation changes.

Introduction

In order to better produce and develop the vast Brazilian pre-salt carbonate reservoirs, several techniques have been studied. Among them, the use of time-lapse seismic data to detect production induced fluid and pressure changes on carbonates. Having achieved success in monitoring offshore Albian carbonate reservoirs (Grochau et al., 2014), Petrobras decided to focus on Aptian pre-salt, stiffer carbonates. The recently completed node acquisition of an important pre-salt oil field is to serve as a base survey and monitor surveys are planned to be acquired starting in 2017. For another giant oil field, the same acquisition geometry is planned to happen soon, followed by monitor surveys in the future. We forecast that the interpretation of 4D seismic data (S4D) on these stiff pre-salt carbonates will not be trivial due to variety of effects, including not only pressure and saturation changes, but also rock-fluid interaction and perhaps, thermic as well. Consequently, in order to better interpret the eventual 4D anomalies, we intend to investigate the added value and limitations of applying spectral decomposition (SD) on 4D data.

In the past, there were few attempts of using spectral decomposition on 4D seismic data. Previous works describe the application of frequency decomposition for S4D data. Zhao et al. (2006) applied SD to a 4D seismic data from the Norwegian North Sea, it is determined the lack of robustness of SD on 4D workflow in high frequencies for difference volumes, and the importance of modeling to correctly interpret results. Rojas and Davis (2009) applied SD on a multicomponent seismic data set in an onshore sandstone to identify faults and fractures. White et al. (2015) applied for CO2 monitoring.

In this paper, we investigate how SD and facies classification can help time-lapse seismic interpretation for a typical pre-salt carbonate oil field, focusing on variations of pressure and fluid saturation changes. Synthetic seismic data were created using PEM and convolutional modeling.

Pre-salt carbonate reservoir characteristics

The field in this study is located in the Brazilian pre-salt province, which has important hydrocarbon volumes due to its thickness and areal extends (Figure 1). The top of reservoir is located approximately 5,000 meters below sea level and sealed by a thick salt layer.

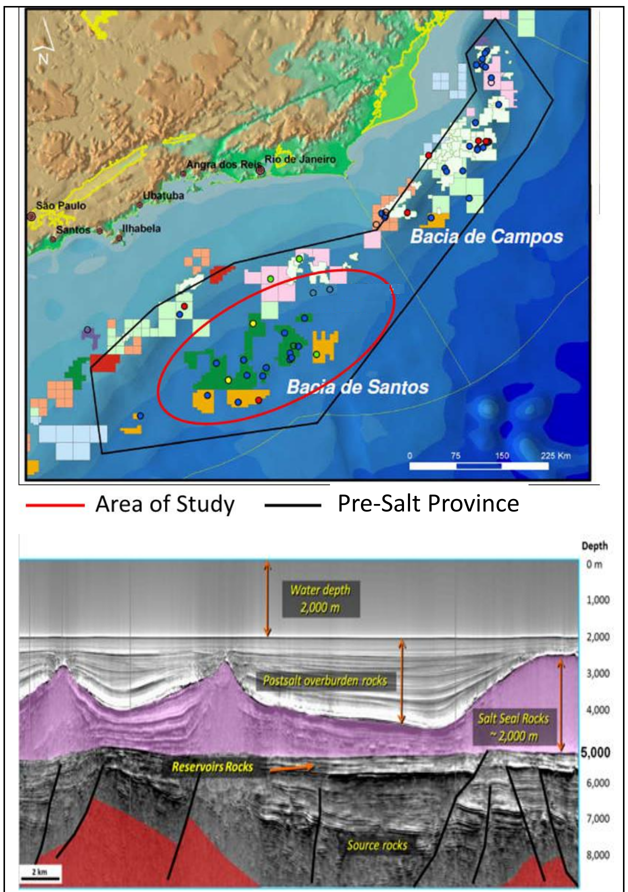

Figure 1: Map of the Brazilian pre-salt province (top), Gaffney, Cline & Associates, 2010; and a typical vertical seismic section showing the main stratigraphic units (bottom). Azevedo, 2011.

Methodology

Spectral decomposition breaks the seismic trace into constituent frequencies, highlighting specific structures that are better represented in discrete frequencies rather than in full bandwidth, defining lateral and vertical borders of depositional packages and sequences (Paryka et al., 1999; Chopra, 2013; Castagna and Sun, 2006). One of the main characteristics extracted from spectral decomposition volumes is the correlation between bed thickness and frequency (Partyka et al., 1999; Khonde and Rasogi, 2013).

Difference volumes (monitor-base) carry information on amplitude, frequency and structural changes between base and monitor surveys. It is expected that spectral decomposition of the difference volume allows detecting structural and amplitude alterations due to production. In real data, along with production induced changes, there may be present acquisition footprints, noise and time shifts. Those factors are not accounted in this study.

Changes in individual frequencies between the base and monitor surveys may be related to absorption with changing saturation fluid (Chen et al, 2008; Castagna and Siegfried, 2003) or structural changes leading to constructive and destructive interferences. The latter is the focus of this study.

1- Petroelastic Modeling

Based on the known geometry and geological properties of the oil field under study, a flow simulation grid was created. For this dynamic flow simulator, elastic properties were forecasted, corresponding to the expected reservoir pressure and saturation distributions for the time of the base and monitor seismic data acquisitions. The changes in saturation and pressure are shown in Figure 2.

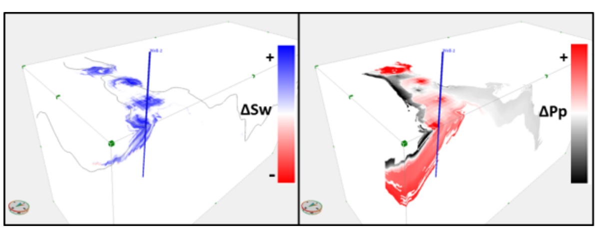

Figure 2: Water saturation increase (left), and pore pressure changes (right) predicted for 2019 to 2022 period.

Having static (i.e. porosity, dry rock incompressibility) and dynamic (i.e. saturation and pressure distribution) properties in each cell of the simulation grid, a PEM was performed to obtain impedances and reflection coefficients. A convolutional forward model and synthetic seismic data were created. Figure 3 shows the synthetic differences between base (B) and monitor (M) volumes generated using a wavelet extracted from real seismic data.

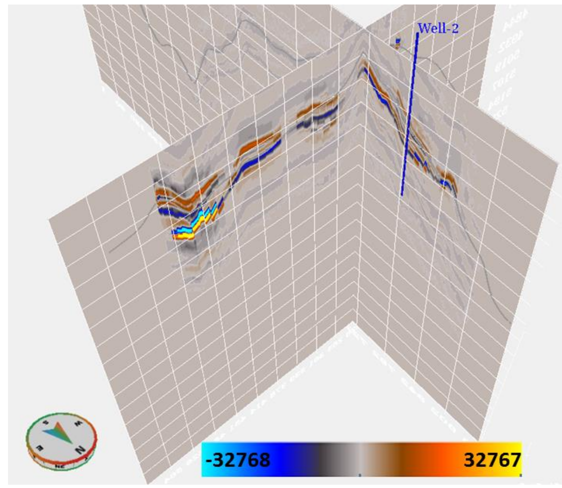

Figure 3: Synthetic amplitude difference generated using convolutional model with central frequency of 12 Hz.

2- Frequency Characterization of Base and Monitor Volumes

The base and monitor frequency spectrums show strong similarity in the reservoir interval: a 14 Hz dominant frequency and a bandwidth of 21 Hz (Figure 4). The largest differences between the base and monitor spectrums occur between 3 and 50 Hz. The difference of the base and monitor amplitude volumes is small and bimodal with peak at 10 and 29 Hz.

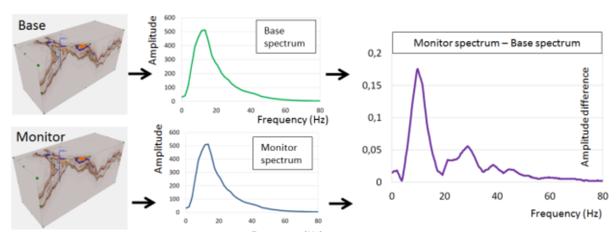

Figure 4: Base and monitor synthetic amplitude volumes (left), their frequency spectrums (middle) and spectral difference (right).

Another way to compare the frequency content between the base and monitor models is by computing the amplitude difference volume and then extracting its frequency spectrum. Figure 5 shows this approach and it can be seen that the difference amplitude volume has a dominant frequency of 14 Hz and bandwidth 25 Hz. Note that there is a relative increase in high frequencies related to the second peak, around 30Hz, seen on Figure 4 (M spectrum minus B spectrum).

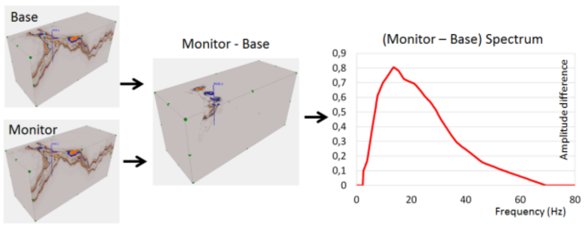

Figure 5: Base and monitor synthetic amplitude volumes (left), the amplitude difference (middle) and its frequency spectrum (right).

3- Spectral Decomposition of the Amplitude Difference Volume

To understand the effect of saturation and pressure changes using SD, two strategies were investigated:

(i) frequency decomposition of the amplitude difference (M-B) volume; and

(ii) the difference between discreet frequencies computed for each volume (B, M) (Figure 6).

As the first approach provided visually better results, regarding 4D seismic anomalies detection, we will focus on that method.

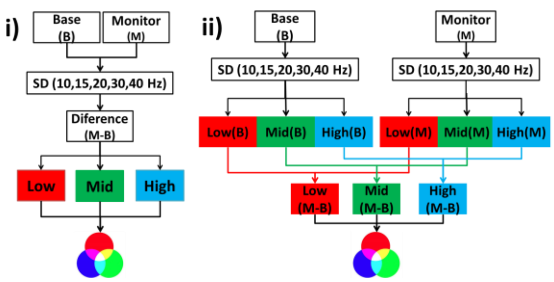

Figure 6 – Two strategies applied for this study: i) SD of the amplitude difference; and ii) SD of base and monitor, and then compute differences between low, mid and high discrete frequency amplitude volumes.

Based on spectrum shapes observed in Figures 4 and 5, the amplitude difference volume was decomposed into 5 discrete frequency amplitude volumes using 10, 15, 20, 30 and 40 Hz Gabor wavelets. Several combinations of these frequencies were blended using a RGB color scheme. Figure 7 shows examples of the mentioned combinations.

4- Facies Classification

In order to deeper investigate SD potential for identifying production derived effects, a facies classification using a probability density function was performed. The aim is to understand if facies mapped in color blends can be used as a proxy for identify changes in petro-elastic properties.

Firstly, the amplitude difference SD color blend was used to perform facies classification using a dominant color pattern (related to frequency) as a main parameter. Secondly, in order to understand the previous step potential in providing useful information, petro-elastic facies are classified according to the known ΔSw and ΔPp relationship. This control information of known saturation and pressure changes will further be called as “reference”. Thirdly, a comparison of the first and second steps is done.

Results

The results presented account for reflectivity interferences generated by both pressure and saturation variations. Seismic dispersion and attenuation are not considered in this stage, once convolutional modeling was used.

Reservoir internal heterogeneities imprinted by ΔSw and ΔPp, due to reflection interferences, are detected and enhanced by the color blends. Tuning effects from the new oil water contact become evident and are shown by the brighter colors (Figure 7, yellow arrows). Applying RGB blends of amplitude differences, SD volumes highlight frequency related changes between the base and monitor surveys, mainly related to structural aspects. Figure 7C clearly shows separations between low and high frequency events (red and blue arrows, respectively).

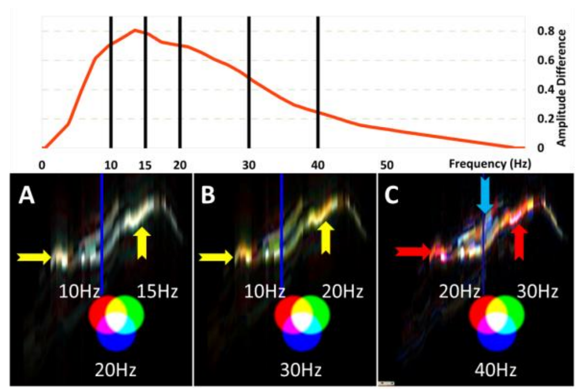

Figure 7 – Vertical sections comparing color blends of discrete frequency volumes. Note that internal heterogeneities are better imaged in the 20-30-40Hz volume (C).

Figure 7 shows boosted signal on the reservoir horizontal limits due to layers tuning. These low frequencies are displayed with white/brownish in 10-15-20 Hz and 10-20-30 Hz (A and B) and by red in 20-30-40 Hz (C).

Internal reservoir layer thickness variation becomes more defined by this particular color assembly (RGB). These variations are mainly generated by constructive and destructive interferences of the reflectors and side lobes, as a result of dynamic properties changes, and thus generating higher frequency images. This statement is related to the relative higher frequency content of the difference volume spectrum compared to the base and monitor (Figures 4 and 5).

In terms of 4D monitoring, it was expected to detect changes in water saturation rather than pressure changes in the stiff carbonates. It can be seen in Figure 8, it is possible to retrieve, using SD, the morphology of the 4D anomaly, which matches the known ("reference") water saturation change.

Spectral decomposed volumes could not improve pressure changes detection in comparison with amplitude data. Low amplitude differences due to pressure changes from the reference synthetic data are not boosted by SD.

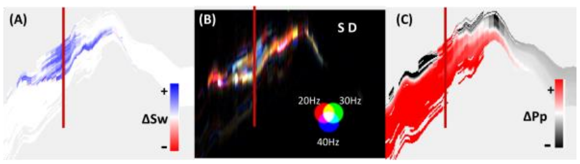

Figure 8 – Vertical section of (A) water saturation change; (B) SD; and (C) pressure change.

Facies classification was then applied on SD data in another attempt to retrieve the "reference" production derived effects. Despite the lack of vertical resolution due to a low dominant frequency, water increase is well correlated with known water changes. Figure 9 compares the "reference" blue facies class (B) with SD (C) and facies classification on the SD data (D).

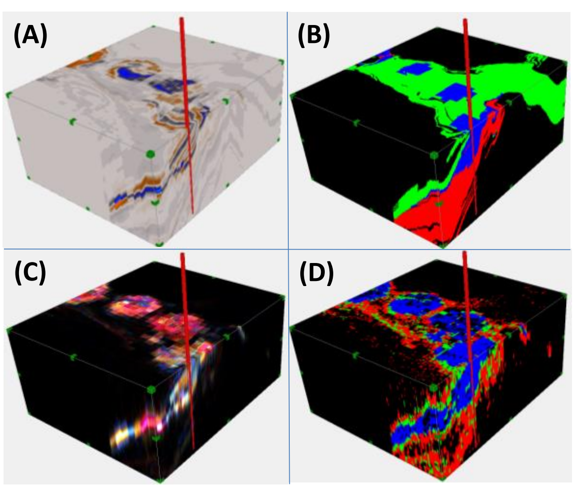

Figure 9 – (A) Synthetic amplitudes difference; (B) "reference" facies classification performed on ΔSw and ΔPp volumes: Sw increase (blue), Pp increase (red) and Pp decrease (green); (C) color blended SD of the amplitudes difference; (D) facies classification performed on the RGB color blend.

Facies corresponding to pressures changes are visible (red and green), however their correlation is weaker with the "reference" petro-elastic model (Figure 9B). This can be explained by the inability in separating between positive and negative values during computation for RGB blending.

Conclusions

Monitoring production derived effects on stiff carbonates is a challenging task, so new approaches of using seismic time-lapse (S4D) monitoring are needed. In this paper, we investigate spectral decomposition of 4D synthetic seismic data generated by petro-elastic modeling using typical Brazilian offshore pre-salt carbonate reservoir properties. The model used to create synthetic data honored the expected in-situ reservoir saturation and pressure distribution during base and monitor surveys. Known static and dynamic properties are used as a reference to evaluate the applicability of SD, and facies classification of SD data, for improving interpretation.

The main results of <u>applying SD on the synthetic data</u> are: (i) reservoir internal heterogeneities, imprinted by dynamic changes due to reflection interferences are better detected; (ii) internal reservoir layers thickness variation becomes more defined by RGB colors assembly; (iii) SD data is morphologically correlated with water saturation increase; and (iv) SD could not improve pressure detection in comparison with amplitude data.

The main results of <u>applying facies classification on the SD data</u> are: (i) the obtained classes related to water increase are well correlated with known "reference" water changes and (ii) classes related to pressure changes have lower resemblance with the known pressure variation.

Next step will be to investigate SD on synthetic data created by point spread function in order to account for dispersion and attenuation. Furthermore, once real seismic data become available, we will use the SD of the base and monitor surveys, and then compute differences between low, mid and high frequency amplitude volumes to discriminate hardening and softening effects.

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EDITED REFERENCES

Note: This reference list is a copyedited version of the reference list submitted by the author. Reference lists for the 2016 SEG Technical Program Expanded Abstracts have been copyedited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

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