Seismic Attributes for Constraining Geostatistical Seismic Inversion

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Abstract This paper aims to constrain the geostatistical seismic inversion method, improving it to match acoustic and/or elastic models with spatial structures interpreted from seismic attribute analysis. A method using seismic attributes as parameters in the objective function was created and inserted within the standard Global Seismic Inversion approach, where the a global perturbation method is done using Direct Sequential Simulation and Co-Simulation as the image transforming technique. Convergence is measured by comparing selected seismic attributes calculated from the synthetic seismic data with those derived from the real seismic dataset. The algorithm was tested on a real case study from a deep-water carbonate oil reservoir. Several combinations of seismic attributes were tested to determine the method's sensibility. The approach presented here can be used to constrain the inherent spatial uncertainty, associated with geostatistical seismic inversion processes with features that are inferred from the seismic signal, the seismic attributes.

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Introduction

By solving geophysical inversion problems one aims to make inferences about physical systems from a limited set of observed data. Inversion problems, and in particular seismic inversion ones, have non linear and nonuniqueness solutions, due to the band-limited nature of the observed seismic data,d, with d Є $\mathbf{R}^m$, where *m* is the number of observations, which are frequently contaminated with measurement errors, **e**. The observed data is related with a model by some physical forward model, a mathematical function *g* that governs the phenomena under investigation. In this framework there are many combinations of *n* unknown Earth model, acoustic and/or elastic models in the seismic sense, **m**, with **m** Є $\mathbf{R}^n$ that fit the data equally, in this case the seismic reflection dataset (Scales & Tenorio, 2001).

The relationship between observed data and the Earth models can be generally summarized by the following equation:

$$\mathbf{d}=g(\mathbf{m})+\mathbf{e} \quad (1)$$

Seismic inversion methods are based on the physical relations between an earth models (acoustic and/or elastic impedance models), which are intrinsic of the subsurface geology, and the seismic amplitudes (the seismic reflection data itself). The latter are obtained through convolution of the reflectivity coefficients, easily derived from the acoustic impedance models, with a known wavelet, estimated from each seismic dataset.

The inversion of seismic data into elastic properties, namely acoustic and/or elastic impedance models, can be posed as a deterministic or a stochastic problem (Bosh, Mukerji, & Gonzalez, 2010). In this paper we will only consider the stochastic framework to solve the inversion problem between seismic data and earth models. To a detailed comparison between deterministic and stochastic methodologies the reader can see Scales & Tenorio, 2001.

Briefly, one can describe stochastic seismic inversion methods as the generation of several realizations of elastic properties, acoustic and/or elastic impedances, with the final purpose of uncertainty assessment of those properties. Seismic inversion methods in this framework are often referred simply as geostatistical seismic inversion methods, when they are based on geostatistical simulations. The importance of these inversion techniques has increased its importance in the oil & gas industry in the last past decades, since it allows the assessment of the uncertainty in reservoir models, leading to better and more reliable decisions.

Since the seminal paper of Bortoli et al (1993), many authors proposed different versions for the geostatistical inversions based on trace-by-trace inversion (e.g. Hass & Dubrule, 1994) or considering a global inversion (Soares, Diet, & Guerreiro, 2007). The new methodoogy proposed here, is based on the Global Stochastic Inversion (GSI; Soares, Diet, & Guerreiro, 2007; Caetano, 2009). In this method acoustic impedance models are generated with an iterative and convergent process of Direct Sequential Simulation and co-Simulation (Soares A. , 2001). The final acoustic impedance models reproduce both the main spatial patterns, as revealed by the variograms, and the probability distributions retrieved from the original well data. With global inversion methodologies areas of poor quality seismic data (with low signal-to-noise ratio) are poorly matched and therefore they reveal areas of increased uncertainty within the resulting earth model (Soares, Diet, & Guerreiro, 2007).

In the improved version of this methodology, proposed in this paper, seismic attributes are included in the object function of the GSI workflow in order to increase the degree of convergence between the observed seismic data and the synthetic one resulting of the inversion process. The use of seismic attribute analysis during this inversion process better constrains the inversion process, as long as non stationary spatial structures are better captured by them, and allows the assessment of the spatial uncertainty of different earth models.

"Seismic attributes" can be described as simple tools to describe and quantify a characteristic content of the seismic data, the result of any calculation that one can do over the seismic signal. In other words, they can be thought as an alternative way to display the seismic data, which is normally displayed in amplitude (e.g. Chopra & Marfurt, 2005).

In this paper we present the outline of the new methodology and its application to a real 3-D seismic dataset from a deep-offshore carbonate reservoir.

Outline of the Proposed Methodology

In this section we briefly introduce the general workflow detailed described in Soares et al (2007), for a deeper explanation, the author is referred to their work.

The regular procedure of the GSI method is based in the Direct Sequential Simulation an Co-simulation (Soares A. , 2001) as the transformation technique of the 3-D images. The workflow comprises an iterative process following the typical approach of genetic algorithms, where the optimization is obtained due to the convergence of the transformed images (a set of synthetic seismic cubes at each iteration step) towards an objective function, that compares the real seismic data with the synthetic seismic cubes computed at each iteration step of the workflow.

At each iterative step the local and global correlations between the synthetic and the real seismic data are computed. The optimization step which assures the convergence is based on the genetic algorithm approach. The "best parts" of the simulated images are used to create a new set of images on the next iteration. The iterative process runs until it converges to a given user-defined threshold . The GSI workflow step can be summarized in the following steps:

i) Generate a set of initial images of acoustic/elastic impedances by using Direct Sequential Simulation from available well log data;

ii) Compute the correspondent synthetic seismic volume, by convolving the reflectivity series, derived from the acoustic impedance models, with a known wavelet, estimated at the well location and representative for the entire field;

iii) Evaluate the match of the synthetic seismograms, of the entire set of simulated images, and the observed seismic by computing local correlation coefficients;

iv) Rank the "best" images based on the match between real and synthetic data. From them, select the best parts of each image, compose one auxiliary image with the selected "best" parts, for the next simulation step, (see point 3 and 4);

v) Generate a new set of images, by direct Co-simulation, and return to step ii) until the objective function reaches a given threshold.

Integration of Seismic Attributes in the Objective Function

The new methodology presented in this paper introduces a new step after ii): a specific seismic attribute is calculated from the real observed seismic data and from the synthetic cubes. In step iii) the match between seismic attributes computed on synthetic seismogramas and real seismic is evaluated and integrated in objective function. In the case study presented below, it was chosen the seismic attribute - Local Variance – to characterize the different spatial structures in the oil reservoir. In the next step iii) the evaluation of the match between synthetic and real data also takes into account, by weighting diferently, the attribute cubes. In the first steps of the iterative process the correlation between amplitudes has a higher weights, than the attributes match. After the first iteration steps the weight associated with the correlation value between the attribute cubes increases. In this way we achieve a good solution for the seismic inversion problem, not only in terms of seismic amplitudes but also in terms of the property that the seismic attribute enhances.

Then, the workflow follows as previously described. A schematic representation of the entire process is shown in Figure 1.

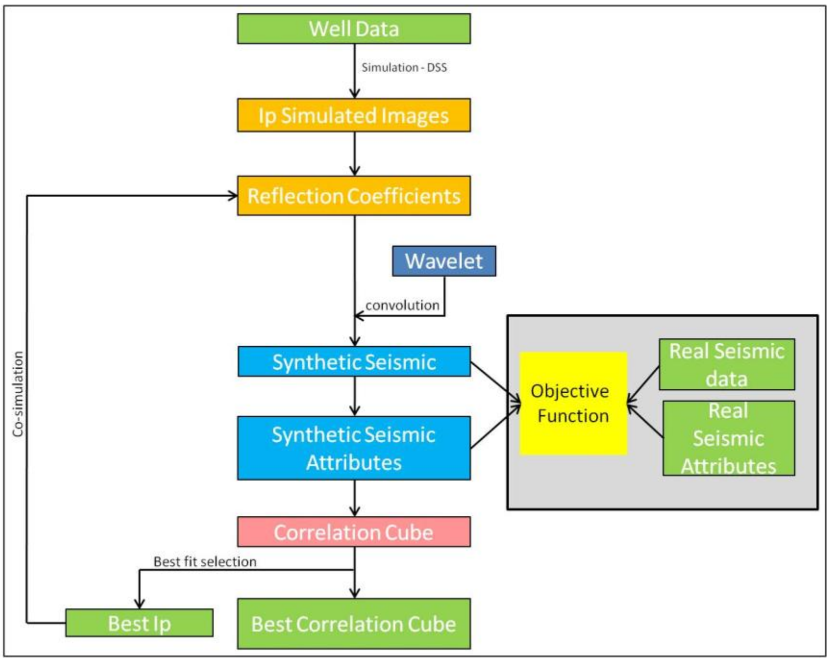

Figure 1 - Schematic representation of the GSI workflow with the new proposed implementation highlighted by the gray box (modified from Caetano, 2009).

Case Study

This new method was applied to an ultra-deep carbonate reservoir, in a very complex geological environment, off E. South America. In this practice example only two wells were available over the study area of approximately 5500km^2, the size of the available seismic dataset to be inverted.

Given the lack of "hard-data" to constrain the seismic inversion process and to model the horizontal spatial pattern of the acoustic impedance for this area a set of different geological scenarios was created and tested. In a first stage the horizontal variography was computed along the original seismic grid, in terms of amplitude continuity. Then, and since the variogram model was build not over the original property, acoustic impedance, but over the seismic amplitudes, 4 different alternative and possible geological scenarios were created according different horizontal variogram ranges (Table 1). The vertical variogram was modeled with the available well data and was considered constant in all the geological scenarios, since we assume to have good representation of the vertical spatial continuity of the property in study (a large number of samples closely spaced).

Examples of vertical and horizontal sections of the original and the final synthetic seismic volumes, for each of the geological scenarios, are shown in figure 2 In general there is a very good match between the original seismic data and the synthetic volumes created after the inversion process.

As expected, with the increase of the horizontal variogram range the structures (seismic reflectors) tend to be more continuous (Figure 2d and Figure 2e) when compared with the original seismic data.

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Table 1 - Summary of the geological scenarios from where the proposed methodology was applied.

Scenario	Horizontal Range (seismic blocks)		Vertical Range (ms)
	Main (E-W)	Minor (N-S)	
1	100	40	70
2	210	78	70
3	300	100	70
4	350	110	70

The final global correlation coefficients between the original seismic data and the synthetic seismic data resulting of the standard Global Stochastic Inversion workflow are summarized in Table 2. Note that in the reservoir zone, where the wavelet was estimated and extracted, the local correlation coefficients reach much higher values.

Table 2 - Summary of the final global correlation between real and synthetic seismic data for each of the geological scenarios.

Scenario	Global Correlation Coefficient
1	74%
2	69%
3	66%
4	64%

Integrating Seismic Attributes in the Objective Function

From the results of table 1, one should choose which one of the scenarios better represents the real subsurface geology. This question is of particular interest for scenarios 1 and 2 where the final global correlation is around 70%.

In order to select the most suitable scenario, and consequently the best horizontal variogram model, a set of different seismic attributes were computed from the original seismic and the synthetic seismic cubes and compared. Tested attributes included those known as Complex Seismic Attributes (related with the different component of the seismic signal) and Structural Attributes (those that are related with the internal organization of the seismic reflectors).

From the set of tested seismic attributes the Local Variance seismic attribute, (Pepper & van Bemmel, 2011) was the one that better reflects the important spatial structures present in synthetic seismograms and in the real seismic data.

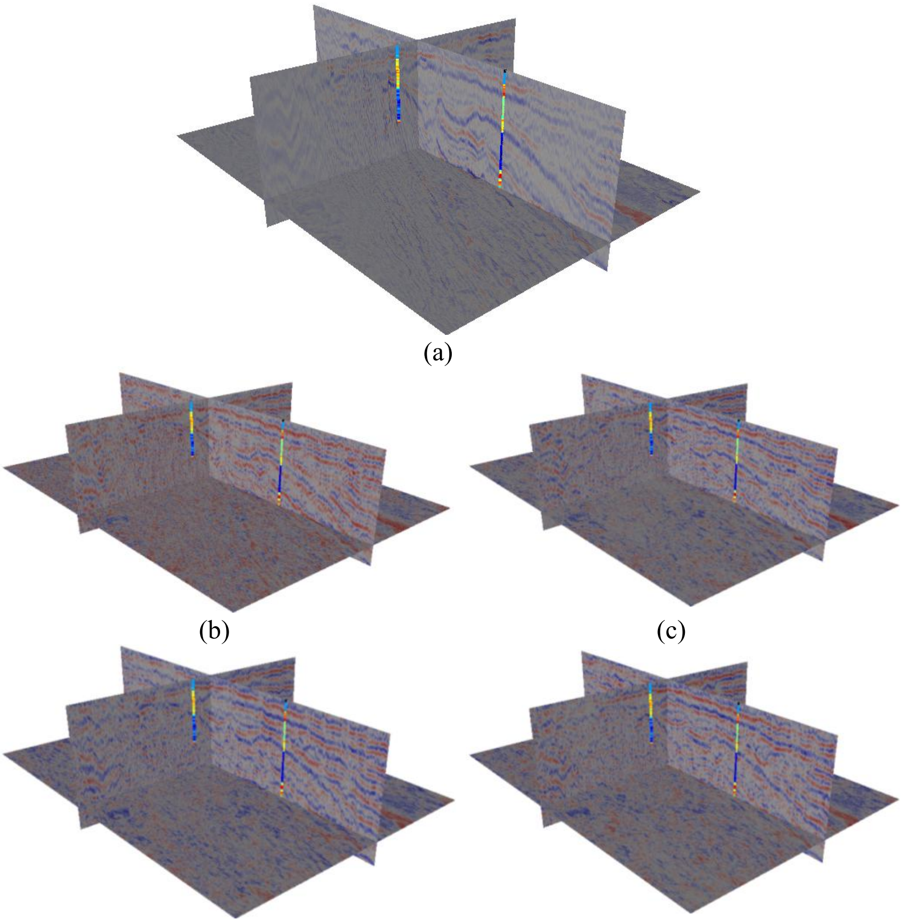
The Variance attribute can be briefly described as the normalized variance computed over time slices along the seismic cube through a multi-trace local window (Pepper & van Bemmel, 2001). In terms, of seismic interpretation, it is a valuable tool since it enhances the presence of spatial continuity patterns and local variable structures (e.g. faults and depositional borders).

Examples of horizontal time slices extracted from the various Local Variance cubes (Figure 3) show that, as the range of the variogram increases (from geological scenario 1 towards scenario 4) the spatial structures of local variance decreases. This effect is clearly observed at the well locations, and when comparing the attribute derived from the original seismic with the ones computed over the synthetic cubes of scenarios 3 and 4. Notice the large circular areas of continuity, low values of Local Variance, around the wells location (Figure 3c and Figure 3d). In the other extreme of the 4 geological scenarios, if one compares the variance extracted from the original seismic with the one extracted from geological scenario 1, the last shows much more small-scale discontinuities than the real case, particularly in the NW part of the study area.

Based on these results, the geological scenario that best fit the real seismic dataset, and consequently the real geological subsurface, is the scenario 2. From here it was decided to include the computation of the Local Variance attribute as part of the Global Stochastic Inversion process (Figure 1).

The new proposed methodology matches not only the amplitude content of the signal but also the internal structure of the reflectors. The structure is measured by the Local Variance attribute and therefore the final synthetic seismic cube, and associated acoustic impedance model, is the one that better fits the structure of the real subsurface geology in this stochastic context.

In addition, the final global correlation between the real and the synthetic seismic data, derived from the geostatistical inversion constrained by the the Local Variance, increased about 10%.



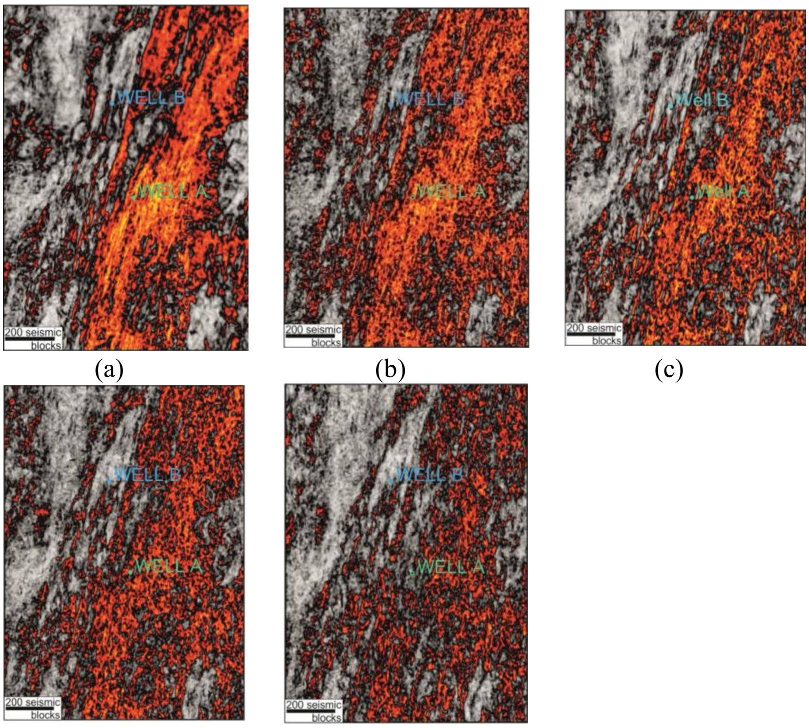
(a) (b) (c) (d) (e)

Figure 2 – Comparison between: (a) real seismic data; and the synthetic seismic data created with the standard GSI workflow for (b) geological scenario 1; (c) geological scenario 2; (d) geological scenario 3; (e) geological scenario 4.

Final Remarks

The integration of seismic attributes in the objective function of the standard Global Stochastic Inversion process presented in this work, allowed a better match between the structure, in terms of seismic reflectors' organization, of the original seismic data and the synthetic seismic data created during the inversion process. Due to this reason they have been included as part of the GSI workflow, which now honors not only the amplitudes of the original seismic data but also the internal structure of the data.

In addition, the use of seismic attributes may be used to distinct and select the best elastic model from a set of different geological scenarios. Note that in the case study presented here the Local Variance was the one that showed the best result in the selection of the best geological model. Nevertheless other seismic attributes can be chosen according the objective of each particular study.



(a) (b) (c)

(d) (e)

Figure 3 - Time slices, at the same time position, from the Local Variance attributes cubes derived from (a) the original seismic data; (b) the synthetic seismic cube from scenario 1; (c) the synthetic seismic from scenario 2; (d) the synthetic seismic cube from scenario 3 and (e) the synthetic seismic cube from scenario 4. Discontinuities values are represented by reds while areas of lateral continuity in terms of amplitude are displayed in white.

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