Expanding the limits of Factorial Kriging applications

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Abstract

Although major care is usually taken during the steps of acquisition and processing regarding the quality of the final seismic data volumes, reservoir geophysicists still face difficulties related to remaining noise and irreducible indetermination, as observed when calibrating seismic-to-well data or interpreting seismic attributes for reservoir characterization purposes. Geostatistics offers alternative methods concerning the analysis of the seismic information, using a probabilistic approach based on the analysis of the spatial variability of the data.

In this paper, the Factorial Kriging (FK) technique is presented and applied in three different aspects in the seismic reservoir characterization workflow: (i) analysis and decomposition of geometrical attributes to improve fracture mapping; (ii) seismic noise characterization to generate more realistic petro-elastic models in time-lapse feasibility schemes; and (iii) improved time-lapse interpretation strategies by FK decomposition. This filtering technique is suited for spatial analysis and it is shown that a great improvement of seismic data quality is achieved.

Introduction

Geostatistics deals with regionalized variables that spread in space. One of its most traditional applications is to provide tools to estimate a variable of interest at unsampled locations, and it is presently a conventional tool to improve static geological modeling. More recently, the oil industry has witnessed the integration of few geostatistical techniques in the seismic reservoir characterization workflows, providing additional tools that helped geophysicists on better understanding the spatial variability of the geological information recorded in the seismic data, particularly in the time-lapse domain.

Conceived by Georges Matheron in France during the 60's, the kriging technique encompasses a family of linear regression algorithms, known as BLUE estimator, an acronym for Best Linear Unbiased Estimator. It is considered to be the best estimator, as the algorithm searches to minimize the variance of the kriging error, usually constrained to be equal to zero.

One particular implementation of this estimation technique is the Factorial Kriging (FK). Originally proposed by George Matheron (1982) in his paper entitled *Pour Une Analyse Krigeante des Données Regionalisées*, the Factorial Kriging technique addresses the problem of decomposing a regionalized variable into a set of orthogonal random functions. Due to this feature, it has been extensively used in many geoscience areas to decompose any sort of images, providing tools to filter them through the resulting orthogonal factors (Sandjivy, 1989; Jugla et al., 2004; Mundim et al., 1996; Abreu, 2008).

The application of the Factorial Kriging technique in this work covers three different aspects in the seismic reservoir characterization workflow: (i) analysis and decomposition of geometrical attributes to improve fracture mapping; (ii) seismic noise characterization to generate more realistic petro-elastic models in the time-lapse feasibility schemes; and (iii) improved time-lapse interpretation strategies by FK decomposition.

Improving geometrical attribute analysis

Among innumerous geometrical attributes available today for the seismic interpreter on modern interpretation workstation software's, the curvature plays an important role on improving faulting and fracturing characterization, particularly when directly computed from 3D seismic data (Roberts, 2001; Klein et al., 2008).

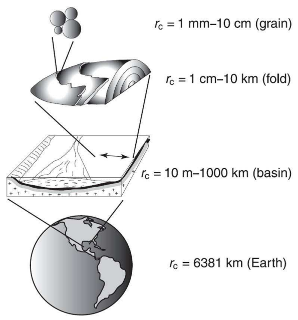

Figure 1 - The final computed curvature is in a fact the sum of curvatures corresponding to distinct spatial scales (from Bergbauer et al., 2003).

The spatial scale of investigation is an important parameter. Curvatures may detect several scales of structural variation, ranging from the surface roughness at very small scale to the large range structuration, as shown in Figure 1 (Bergbauer et al., 2003). In order to focus on the structural information that is relevant to the problem under investigation, it is crucial to discriminate the different spatial scale levels of the curvature attribute map. Geostatistics offers efficient methods for the spatial analysis and decomposition of the main curvature attributes, in order to improve its structural interpretation.

The interpretation of such attribute, however, is often complicated by the presence of undesired artefacts related to poor seismic quality areas. Noise in the seismic volume is usually translated to the derived curvature as very small-scale variation components, and results in more complex curvature attribute maps.

Proposed Methodology

The proposed methodology flowchart is illustrated considering the curvature attribute computed on a 400km^2 area of a deepwater reservoir from offshore Brazil. Most positive and most negative curvatures were computed in 3D, using the time-migrated seismic amplitude volumes and extracted for interpretation along the time interpreted structural maps.

The spatial quality control of curvature maps relies on the results and the interpretation of a 2D geostatistical analysis of the curvature attribute maps, and was independently performed for each principal curvature attribute map as follows:

- Experimental variograms are computed in the main horizontal directions together with standard histogram and usual statistics to analyse the distribution and spatial behaviour of the data set. The variogram provides a quantification of the data variability as a function of the lag distance *h*. The experimental variogram $\gamma(h)$ is classically computed from sample points as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{x_i - x_j \sim h} [z(x_i) - z(x_j)]^2 \qquad (1)$$

  where $N(h)$ is the number of pairs of points (x_i, x_j) separated by the vector distance h in the summation.

- Then, the spatial ranges identified on the experimental variogram are interpreted in terms of consistent spatial structures or seismic artefacts, during the structural analysis step.

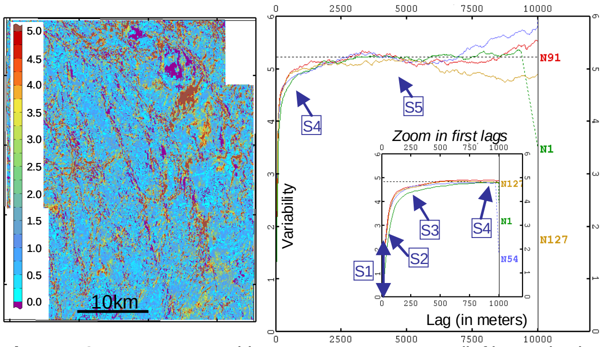

Figure 2 - Most positive curvature map (left) and the correspondent experimental variograms computed for four different horizontal directions (right).

Figure 2 presents, on the right, the experimental variogram of the most positive curvature, computed along four main horizontal directions and considering a range of investigation of 10.000m. A zoom of the first 1.000m is also displayed on the right side. The experimental variograms were interpreted in terms of spatial structures as follows:

- A preferential continuity along the crossline direction, which accounts for 17% of the global variability, named Structure 1 or S1;
- A 50m-range spatial structure, accounting for 17% of the global variability, interpreted as a very small-scale spatial artefact, named Structure 2, or S2;
- A 120mx150m-range anisotropic spatial structure, accounting for 51% of the global variability, interpreted as structurally-consistent, named S3;
- A large-scale 900m-range spatial structure, accounting for 9% of the global variability, named S4; and
- Larger-scale variations, over 3km-range, accounting for 6% of the global variability, named S5;

- The experimental variogram is modelled in such a way that will reflect the previous interpretation of the spatial ranges. This variogram model is the sum of nested structures, and is typically written in terms of covariances as follows:

$$C(h) = C0 + \Sigma Ci(h) \qquad (2)$$

- The spatial decomposition of the curvatures is performed using the Factorial Kriging approach (Matheron, 1982), and is based on the assumption that a regionalized phenomenon can be seen as a linear sum of various independent sub-phenomena acting at different scales, each of which presenting its own variogram model. These independent variograms will, when linearly summed, comprise the variogram model of the regionalized phenomenon.

  The factorial kriging allows to estimate each individual spatial component according to its variogram model. The curvature attribute map is assumed to be split into the sum of its spatial components. The spatial components are assumed to be non-correlated to each other.

Successive factorial kriging procedures are run on the curvature attribute map in order to estimate separately each spatial component at each data location.

Results

Spatial analysis and decomposition are performed independently on the most positive and most negative curvature attributes.

The Gaussian curvature is then computed as the product of the most positive and most negative curvature for each consistent spatial range. The impact of the spatial filtering of the curvature attributes on the resulting Gaussian curvature is analysed.

In Figure 3, a comparison of the raw Gaussian curvature with the Gaussian curvature associated to the small-range spatial components (100m-range and spatial trend) and with the Gaussian curvature associated to the large-range spatial components (900m-range and spatial trend) is presented.

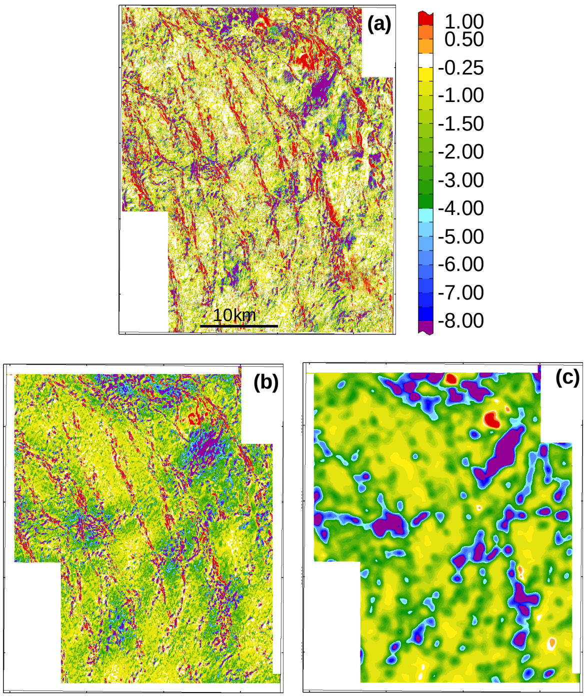

Figure 3 - Gaussian curvature computed using: (a) raw curvature maps; (b) small-range spatial components (100m range and trend); and (c) large-range spatial components (900m range and trend).

The spatial decomposition of the most positive and most negative curvatures leads to the separation of the spatial components in the resulting Gaussian curvature. The small-range components clearly show lineaments most probably associated to the major faults, whereas the large-range components highlight regional flexures, mainly related to most possible fractured area.

The joint analysis of the different curvature attribute maps (most positive, most negative, Gaussian curvature and derived shape interpretation) enables to interpret the structural map in terms of fault delineation, and fracture density.

Artifact simulation for 4D feasibility workflow

The main objective of a time-lapse seismic feasibility study consists in evaluating the elastic and acoustic seismic responses associated to different production scenarios, as predicted from reservoir flow simulators. With this data in hand, reservoir geophysicists may determine the more likely dates to acquire monitor data. 4D seismic modeling workflow is well defined and leads to relevant 4D synthetic seismic models. However, one main difficulty lies on the comparison of the modeled data with the real 4D response, mainly due to difference of spatial quality between real and synthetic seismic. When interpreting real data, different artifacts of various origin may blur the analysis and difficult a proper correlation with reservoir properties. On the other hand, the generated synthetic models usually appear much more smoothed than the real data. To improve the synthetic data interpretation and its comparison with real ones, the proposed challenge consists in adding a *as realistic as possible* artifact to the petro-elastic model, in order to generate "true" 4D synthetic volumes.

Geostatistics, through the variogram analysis, enables to identify the spatial signature of the artifact on real seismic data, and to generate by stochastic simulations spatially consistent artifact volumes.

Proposed Methodology

The artifact simulation flowchart is illustrated in another deep water oil field, from Campos Basin, offshore Brazil. In this case, a time-migrated amplitude seismic volume was considered, and the studied reservoir interval ranges from 3000 to 4200ms, as shown in Figure 4, below.

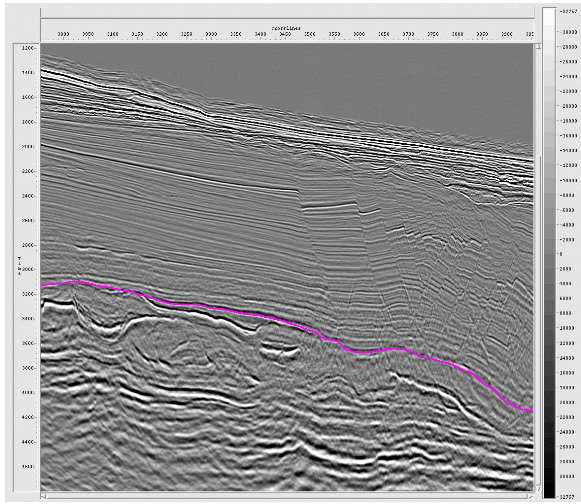

Figure 4 - Inline seismic section, where the Top Reservoir is represented as a pink horizon. Vertical scale in ms.

In a first step, it is necessary to define the statistical and spatial distribution required in the final artifact volume. For this purpose, a spatial quality control is performed on a 2D amplitude map of the "real" base survey seismic data.

The analysis of the experimental variogram computed on the amplitudes along the main horizontal directions enables to interpret it in terms of "possible artifacts" and "geological" spatial structures.

In Figure 5, the raw amplitude map and the experimental variograms computed along the 4 main horizontal directions are presented. The experimental variograms were interpreted in terms of spatial structures as:

- Small-range spatial structures (crossline effects, 100m and 200m-range structures), interpreted as related to small-scale spatial artefacts;
- Medium-range and large-range spatial structure (700m and 1km-range structures), interpreted as geologically-consistent structures.

The experimental variogram is then modeled by adjustment of specific covariance models according to the interpretation of the different spatial ranges.

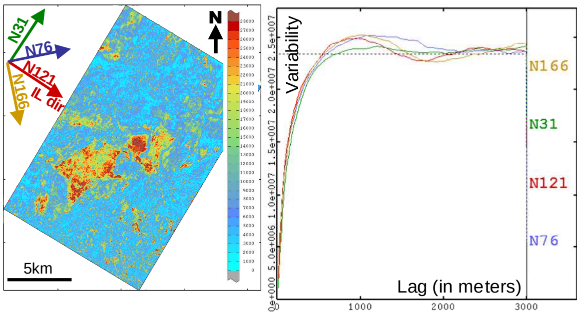

Figure 5 - Raw amplitude map and corresponding experimental variograms computed along the 4 main horizontal directions

In a second step, several 3D non-conditional stochastic simulations are performed using the variogram model of the real seismic artifact to obtain several realizations of the 3D artifact volume. The goal of the stochastic simulation is to generate independent realizations of the given random function model, respecting the imposed statistical and spatial distribution.

Results

The resulting artifact volumes, considered as white noise, are then added to the synthetic model based on different NRMS level. In Figure 6, the resulting 4D synthetic models without noise (a), is compared with the same model after summing a classical random noise (b) and with the geostatistically-generated artifact (c). The 4D signal observed using geostatistical noise seems to be more coherent with the 4D signal generally observed on real 4D survey.

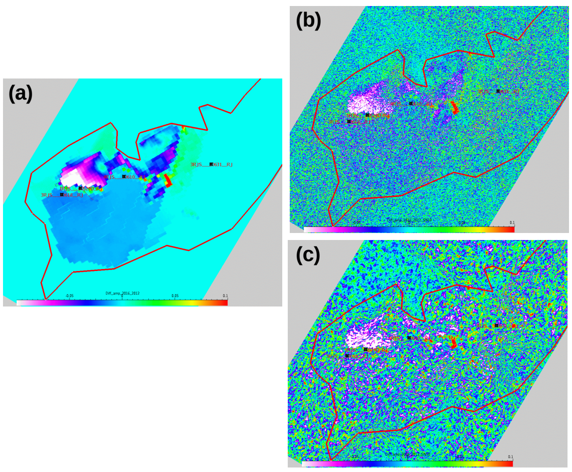

Figure 6 - Three steps of the resulting 4D synthetic model, represented (a) without any noise (b) adding a random or white noise; and (c) adding geostatistically generated artefact.

Producing realistic 4D noisy helps the analysis of the 4D response on real dataset, and provides important clues to the reservoir geophysicists to better understand time-lapse data.

4D geostatistical filtering

The repeatability of the seismic acquisition and processing is far from easy due to the variations of the specific acquisition conditions. It is of primary importance to assess and control the quality and amplitude content of time-lapse seismics in order to enhance the 4D signature.

Geostatistics provides suitable techniques to perform a robust time-lapse coherency analysis: quantify the 4D repeatability between the 2 seismic vintages, using individual and cross- statistical and spatial analysis, and improve it by performing relevant spatial filtering.

Proposed Methodology

The 4D geostatistical filtering flowchart is illustrated in a deep water turbiditic oil field, offshore Campos basin, Brazil, at two different times of the reservoir life, before and after production and water injection, as shown in Figure 7.

Two specific time-intervals are considered: one from a non-productive area, preferentially above the reservoir, not impacted by production effects, and the other comprising the reservoir of interest.

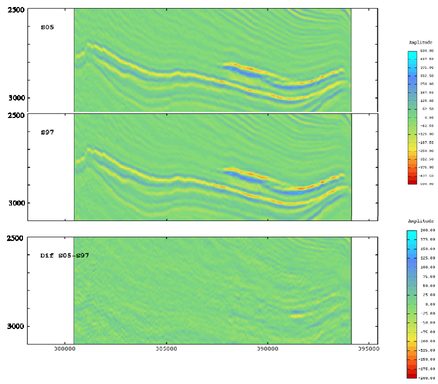

Figure 7 - Seismic sections referred to the base survey (top), monitor survey (middle) and the difference (bottom).

The geostatistical 4D flowchart involves the following steps:

- Spatial diagnostic of the 4D repeatability of the time-lapse seismics. It consists in a comprehensive geostatistical analysis of both the amplitude maps and the full-stack volumes. It involves classical statistics, experimental variogram and cross-variogram amplitude computations. This spatial diagnostic is first performed on the non-reservoir area (not affected by production effects), and then on the reservoir interval. The analysis must be performed on laterally consistent intervals, preferentially by flattening the dataset following a specific stratigraphic marker, or by performing horizon-guided analysis.

This analysis leads to the definition of the main spatial structures present in the data: a special attention is devoted to the analysis of the “natural” spatial structures identified in the amplitudes, and the identification of potential physical processes that could explain these interpreted data.

- The Factorial Kriging technique is applied to the seismic volumes, and the resulting factors are then interpreted in terms of potential 4D effects, or any other type of seismic event, such as noise, regardless of its origin (seismic acquisition or processing);
- The unwanted factors are at last filtered, as shown in Figure 8, below.

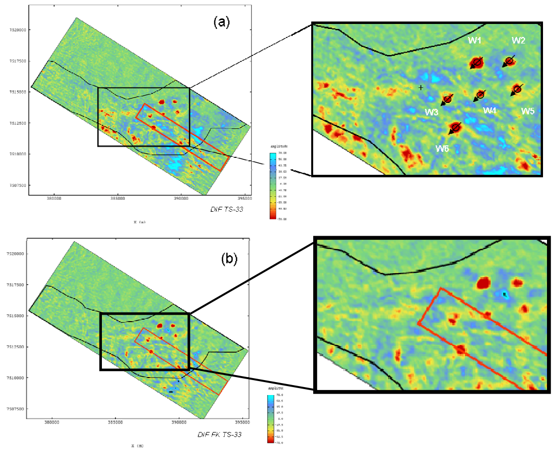

Figure 8 - Horizon-guided amplitude maps extracted close to the reservoir bottom from raw difference data (top) and after performing FK (bottom).

Results

A new methodology based on the filtering of the difference seismic amplitude cube rather on the raw data was suggested. This procedure gives better result as long range spatial structures commonly recorded in the various vintage datasets, usually related to sedimentary imprints or geological structures, are eliminated. Only the acquisition noise or the investigated 4D effects are preserved, as reported in previous work by Calvert (2005).

Conclusions

This paper presented several applications of a geostatistical analysis technique, known as Factorial Kriging, that showed to be an alternative method for the analysis of seismic data. As shown, this technique may be used at various steps of the reservoir characterization and monitoring workflow.

The common point behind these applications is the structural analysis, or variogram and cross-variogram interpretation. In fact, the key issue of the methodology lies on the variogram interpretation, enabling the identification and the decomposition of the dataset variability in separate spatial scale components.

This spatial approach contributes to improve the analysis of the seismic data, focusing on relevant information by filtering possible artifacts, and therefore bringing additional value to the seismic information.

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References

Abreu, C.E.B.S., 2008. Time-lapse (4D) seismic interpretation methodologies based on kriging analysis: application to the Senlac (onshore Canada) and Marlim (offshore Brazil) heavy oilfields. PhD Thesis, INPL-Nancy, France, 332p.

Chopra, S., Marfurt, K.J., 2007. Volumetric Curvature and Reflector Shape. In: Seismic Attributes for Prospect Identification and Reservoir Characterization. Geophysical Developments Nº11, Chap. 4, p.73-98.

F. Jugla, M. Rapin, S. Legeron, C. Magneron, L. Livingstone, 2004. Improving seismic repeatability using factorial kriging - EAGE PARIS 2004

Klein, P., Richard, L., James, H., 2008. 3D curvature attributes: a new approach for seismic interpretation. First Break 26, p.105-111.

Matheron, G., 1982. Pour une analyse krigeante des données régionalisées. Report N-732, CG, Paris School of Mines, Fontainebleau, France.

Mundim, E.C., Johann, P. and Remacre, A., 1999, Factorial kriging analysis: geostatistical filtering applied to reservoir characterization. The Leading Edge, 18, p.787-788.

Roberts, A., 2001. Curvature attributes and their application to 3D interpreted horizons. First Break 19.2, p.85-100.

Sandjivy, L, 1987, Analyse Krigeante des Données de Prospection Géochimique. PhD Thesis, Ecole des Mines de Paris, France, 166p.