Local Stationary Modeling for Reservoir Characterization

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Abstract

When dealing with reservoir characterization using seismic, whatever the algorithm used for inverting the seismic data into reservoir properties, one has to deal with the fact that the reservoir properties varies in space in a way that is controlled by the structural features of the reservoir.
There are basically two ways to deal with this kind of non stationarity of the reservoir properties:
1/ steer the inversion algorithm with a number of moving parameters taking the structural features into account at a local scale
2/ work on the coordinate system to handle the structural non stationarity The paper shows that only the structural anamorphosis of the coordinate system opens the way to a correct implementation of local stationary models
In other words working with moving steering of algorithms will create artifacts as soon as the ranges of reservoir property variations become larger than structural ranges.

An example taken from actual seismic attribute processing illustrates the case.

Introduction

The use probabilistic models [1], [6], [7], [8] represent a good alternative to classical filtering methods and more generally in reservoir characterization (or seismic inversion) [9]. The main advantage of these models is the fact that they provide a best linear estimation of the signal and its uncertainty. Implementation of these models in seismic image processing (filtering, noise attenuation, de-convolution, stochastic seismic inversion) is conditioned by the structure of the geology. In general the application of these models requires some conditions such as local stationarity which is characterized by the covariance model. Usually this can be reached by partionning the seismic image in homogenous regions (layers) in which the statistical parameters can be considered stationary. However this partitioning need a prior geological model which in the early stage of the processing is not yet available. For dealing with this difficulty, geostatistical algorithms are extended in order to integrate the local variation of geostatistical parameters or more precisely the variogram parameters are estimated at each location and then used to build the local estimator (kriging) [2], [3], [4]. From theoretical point of view these models are absolutely valid but the main problem remains in the definition of the covariance (variogram) parameters. We will illustrate by a simple example that the structural (geometrical) control or the varying anisotropy can not be modeled by a simple mapping of the angles (dip, azimuth) but needs a more accurate local geometrical transformation based at least on a roughly defined geometrical structure.

Probabilistic Model

Mainly a kriging based probabilistic model is defined as a linear estimation (1) of a given Regionalized Variable $Z(p)$ sampled in some locations $p_j \;\; j=1,...N_p$.

$$Z^*(p_0)=\sum_{j=1}^{N_p} Z(p_j)\cdot\lambda_j \quad (1)$$

$$Var\left(Z^*(p_0)-Z(p_0)\right)\to \min \quad (2)$$

By minimizing the variance of estimation (2) we obtain the kriging system (3).

$$\sum_{i=1}^{N_p} C_{lhs}(p_i,p_j)\cdot\lambda_i = C_{rhs}(p_0,p_j) \text{ for } \forall j\in[1,N_p] \quad (3)$$

The functions: $C_{lhs}(p_i,p_j)$, and $C_{rhs}(p_0,p_j)$ represents the covariance two point functions and their definition depends of the type of kriging (factorial kriging, de-convolution, co-kriging). For giving a more precise explanation, let's take the case of factorial kriging used for filtering the signal from the noise of a seismic image [6]. In this case the $C_{lhs}(p_i,p_j)$ will present the covariance of signal plus noise and the $C_{rhs}(p_0,p_j)$ the covariance of the signal. By solving the system (3) we obtain the estimated value and kriging variance of estimation (4):

$$\begin{cases} Z^*(p_0)=\sum_{j=1}^{N_p} Z(p_j)\cdot\lambda_j \\ \sigma^2_{krig}(p_0)=C_{rhs}(p_0,p_0)-\sum_{j=1}^{N_p} C_{rhs}(p_0,p_j)\cdot\lambda_j \end{cases} \quad (4)$$

As can be observed, the kriging system id fully defined by the covariance functions and a given neighborhood used for building the estimator. The choice of covariance functions depends on the nature of the estimated variable but also on the mathematical constraint which limits this choice only to the positive definite class of functions in order to insure the fact that the estimated variance has to be positive [1].

An other observation is the fact that the kriging is a local estimator so if we have the possibility to define a covariance function with locally varying parameters we can model spatial variables with a high degree of complexity conditioned by the geological structure.

The simplest way for doing that is to define a local stationary covariance model (5) in which the parameters such as range or anisotropy angles and are modeled as a functions of the location of the estimation point [3], [4]:

$$C(p_i, p_j) = C\left(p_i, p_j, r(p_0), \alpha(p_0)\right) \quad (5)$$

The use of this kind of covariance model is simple to implement but in some practical applications this is not sufficient for handling high oscillations of the geometry and long range continuity of estimated variable. This is often the case of seismic images. The reflectors must have a large extension (long correlation range of the signal) but a short range correlation of the geometry.

For dealing with this difficulty some improvements are proposed [2] based on the computation of a non-Euclidian distance which is more accurate but in practical applications with large seismic images this method has a very important computing cost.

One other way which provides a more efficient covariance definition is the use of local geometrical transformation [6].

$$C(p_i, p_j) = C\left(\psi_{st}(p_i), \psi_{st}(p_j)\right) \quad (6)$$

The geometrical transformation function (6) is defined locally using local geometry of the horizons.

$$p^t = \psi_{st}(p) \quad (7)$$

These horizons don't have to be fully defined as usually in a numerical geological model but by a simple automatic segmentation processing [5].

Synthetic Example

Local definition of the covariance (variogram) parameters such as range sill and anisotropy provides a flexibility for modeling random fields witch the spatial characteristics are not stationary. In the practice one simple way for modeling this stationarity is the partitioning of the estimation domain in several units (layers, regions) in which spatial characteristics (variogram parameters) are assumed to be stationary. However, in many situations this partitioning is not appropriate du to the fact that these parameters can change gradually and the definition of homogeneous regions can't be possible. The simple way to deal with these situations is to realize first an estimation of these parameters in space and then define a local covariance (variogram). For a parameter such local sill this can be done easily without any theoretical difficulty but for the parameters such ranges and anisotropy that can be more critical.

For illustrating this, let's take a simple synthetic example. In the figure 1 is presented a simple area (100x100 units) where a Gaussian Random Field (GRF) is defined in a way that the fluctuations in space follows an alignment controlled by two oscillating curves.

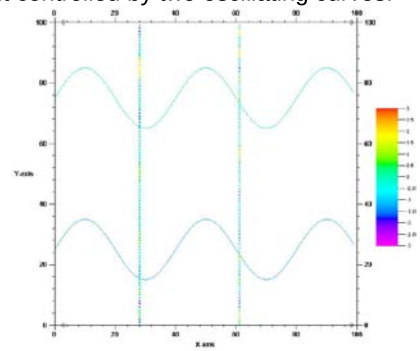

Figure 1 (a) Example of a Conditional Random Gaussian Field generated with Sequential Gaussian Simulation algorithm: a) Conditional data and structural lines

Two vertically aligned dots represent the data samples where this GRF is known. The variogram is defined as a Cubic type with a "horizontal" range equal to 30 and the vertical range equal to 5 units. The algorithm used for generating a realization of this Conditional Gaussian Random Field is the Sequential Gaussian Simulation (SGS). The advantage of this algorithm is the fact that any grid node is simulated by applying a local kriging using a local neighborhood with a locally defined covariance. The image figure 1 (b) shows one realization of this Gaussian Random Field using a local covariance with a varying azimuth. As you can observe, the behavior of the GRF is almost controlled by the geometry (structure) but some artifacts are visible here because the variation of the geometry is much higher than the fluctuations of the property. These artifacts are more important when the wavelength (range) of geometrical oscillations (structure) is lower than the range of GRV.

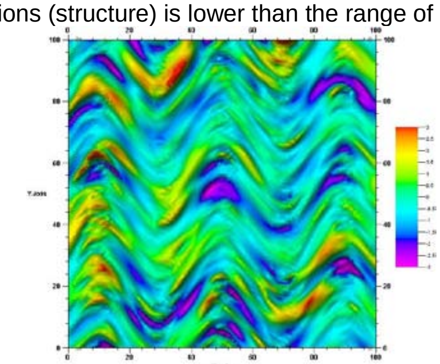

Figure 1 (b) Example of a Conditional Random Gaussian Field generated with Sequential Gaussian Simulation algorithm: b) Simulated field realized using local varying angle

The image in the figure 1 (c) shows the same GRF realized with the same algorithm but the only difference is the way how the local covariance is defined. Instead of using a local azimuth which remains constant for all points in the local neighborhood a local geometrical transformation function is defined in order to apply a local "deformation" of the geometry. The distance between points in the neighborhood is not Euclidian in the real space but in the transformed domain.

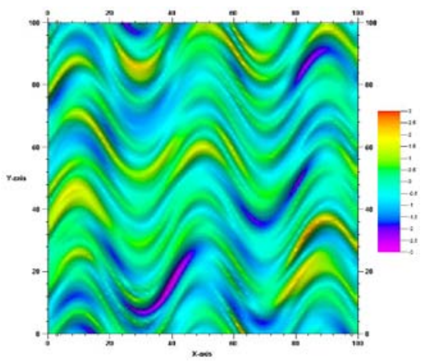

Figure 1 (c) *Example of a Conditional Random Gaussian Field generated with Sequential Gaussian Simulation algorithm: c) Simulated field realized using structural coordinate's transformation.*

Applications on Real Data

One of most difficult aspects of application of kriging operators for seismic image filtering is the geometrical (or structural) control. In the early stage of the processing the structural model is not yet available so the only way for defining the geometry is the seismic image itself. A simple way for extracting the structure is the application of automatic segmentation techniques which provides a partial but fast and sufficient layering behavior of geological structure Figure 2 (a, b) [5].

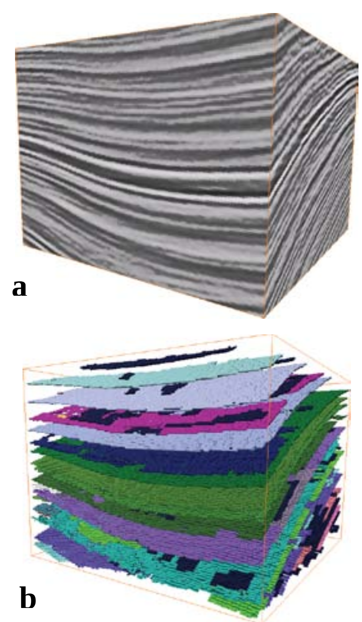

Figure 2 *Example of automatic segmentation: (a) amplitude seismic cube, (b) resulting labels corresponding to the maxima of amplitude ([5],* Sandjivy L., Faucon T., 2007)*.*

The automatic segmentation (Figure 3) can be used for computing the structure consistent variogram parameters and in the same time for defining the local geometry transformation (Figure 4).

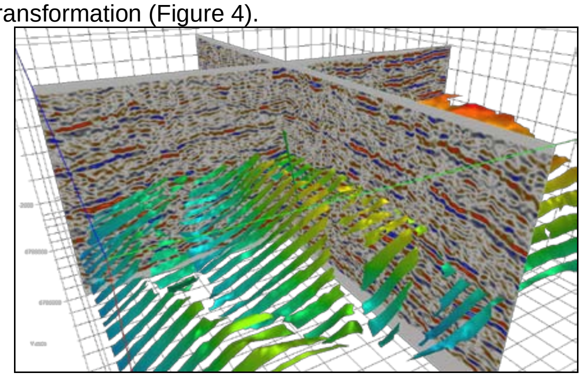

Figure 3 Post stack seismic amplitude 3D cube and an automatically detected reflector.

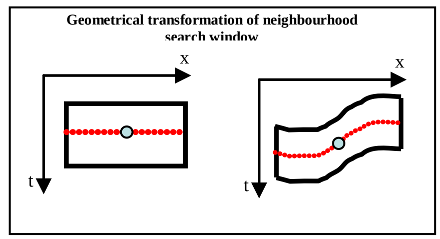

Figure 4 *Geometrical transformation of neighborhood search window in function of the shape of interpreted horizon.*

This local geometrical transformation is defined by a simple vertical shift computed using upper and lower segmented "horizons". The neighborhood window is then deformed in time space in order to respect the layering but without doing any interpolation or re-sampling of the original image.

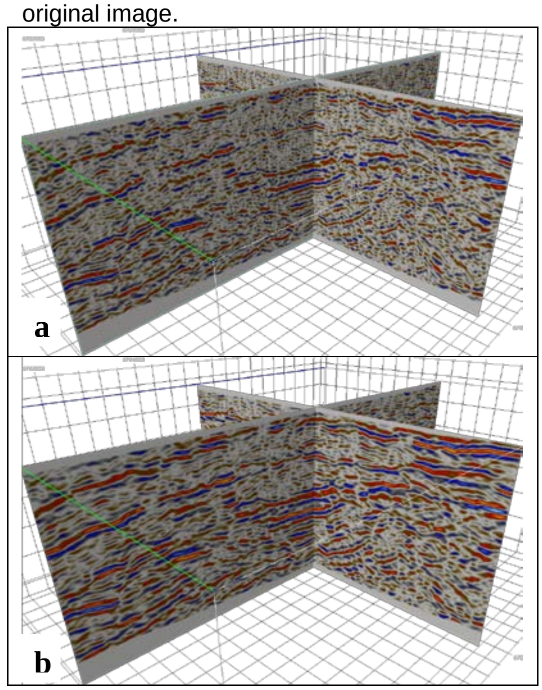

Figure 5*.Comparaison of raw amplitude (a) and filtered amplitude (b) using factorial kriging with structural control.*

Conclusions

Application of probabilistic models in seismic data processing or inversion needs a better structural control based on the geometry of the geological structure. In the early stages of the processing of seismic images this structure is not necessary modeled yet so the implementation of kriging based algorithms needs a better geometrical control based not only in the locally varying covariance parameters but also on an appropriate geometrical transformation. In this paper we illustrate the artifacts introduced if this structural transformation (anamorphosys) is not considered. By associating automatic segmentation techniques, local geometrical transformations and classical kriging based algorithms the obtained results are more reliable respecting in such way the internal structure of estimated geological variable.

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