Geostatistical Inversion: a new methodology for thin beds reservoir characterization

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Abstract

This paper presents the geostatistical inversion methodology and discusses the use of this technique to improve thin bed reservoir characterization.

We begin by discussing the theoretical aspects formulated by *Bortoli et al* in 1993. Then, we show, step by step, an application of geostatistical inversion in a turbiditic reservoir located offshore in Campos Basin.

Finally, we compare geostatistical with sparse-spike inversion, discussing aspects of the reliability of thin beds models and uncertainty analysis.

Introduction

The use of seismic data as a reservoir characterization tool has, nowadays, been widely established due, specially, to data quality improvement, provided by new processing techniques and the geostatistic. Geostatistic allows the integration of seismic data in the quantitative estimation of reservoir properties.

Nevertheless, a challenge remains towards modeling and delimitating thin beds reservoirs. The question is how to build up reliable models for subseismic thin beds reservoirs. That is a real problem for a great part of Brazilian reservoirs which present great amount of oil in reservoirs which are less than 10 meters in thickness.

Another important issue is how to model potential flow barriers among draining units which are not detectable by seismic.

Although a complete solution has not been provided, such problem may be minimized by algorithm and actions in seismic data acquisition, processing, interpretation, and seismic-well integration.

This paper presents a geostatistical inversion algorithm and discusses its applicability as a possible way of addressing this issue.

The results obtained by this algorithm in an offshore field in Campos Basin are compared to the ones attained by a conventional *Sparse-Spike* inversion algorithm.

Method

Geostatistical Inversion or Stochastic Inversion may be seen as a methodology for obtaining a high resolution acoustic impedance volume from a random stochastic variable – the acoustic impedance - acquired in the well logs (sonic and density). It differs from conventional inversion techniques (seismicstatigraphic inversion, *sparse-spike* inversion) in not searching an optimal solution, since seismic data does not present a unique solution in terms of acoustic impedance, but rather provides the possibility of accessing an unlimited number of stochastic variable realizations. In this algorithm, seismic trace role is classifying each random variable realization (well acoustic impedance) as reliable or not reliable.

As originally conceived by Bortoli et all (1993), the basic idea of this methodology consists in selecting among the well acoustic impedance realizations of a Sequential Gaussian Simulation (SGS) the one which shows the best seismic fit in a convolutional modeling. The original algorithm is based upon a trace by trace optimization of the fit of the synthetic seismic obtained by simulation and the real seismic data, rather than a global search for the best image (Haas & Dubrule, 1994). Impedance is obtained by stochastic simulation on a trace, giving rise to an impedance *log*. A synthetic trace obtained by the convolution between the *wavelet* with the series of reflection coefficients related to this pseudo-*log* is compared to the real seismic trace and classified in terms of some similarity criterion. If it is accepted, the algorithm incorporates the simulated *log* to the data and proceeds to the next trace. Otherwise, another simulation of the same trace is undertaken.

The algorithm steps are:

1. obtaining a *wavelet* W which provides the best fit of the well data synthetic seismogram S_{sin} to the real seismic data S_{real};
2. modeling the variogram;
3. drawing a *grid* position by random path;
4. simulating the impedance log I(t) in the time interval;
5. calculating the reflectivity coefficient series R(t);
6. generating the synthetic trace S_{sin} by convolving R(t) with the *wavelet* W(t);
7. comparing S_{sin} to the real data S_{real};
8. if S_{sin} is similar to S_{real}, S_{sin} is incorporated into the data, otherwise another I(t) simulation is undertaken.

It would not be perfectly accurate to classify such methodology as an inversion technique, but it should rather be described as a well impedance log simulation constrained by the seismic trace. Such stochastic process is then not only controlled by the well impedance logs, the variographic model and by the histogram, but crucially also by the seismic trace, so that the number of possible outputs in the solution space is reduced, as seen in Figure 1.

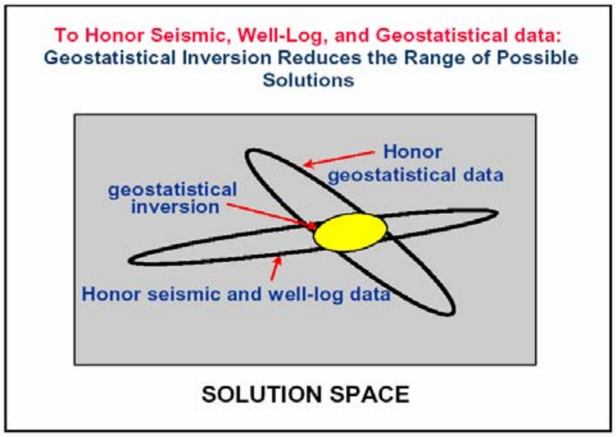

Figure 1 – The space solution of the goestatistical inversion must honor the seismic data, well logs, geostatistical relationships reducing the number of possible solutions (In Torres-Verdum, 2001)

The results presented in this paper were obtained with a different algorithm implemented by *Jason® Geosystems* in the following way:

1. first of all, a well impedance SGS simulation is performed in order to fill the whole grid (a co simulation with a secondary variable is also possible);
2. each grid node is revisited in a random path and resimulated;
3. two synthetic seismograms of the trace are built up; the first one from the original impedance value and the other one from the resimulated value;
4. the correlation between the two synthetic seismograms and the real seismic data is checked;
5. the seismogram with the best correlation coefficient is chosen;
6. a new point is drawn in a random path.

The algorithm stops when a good correlation coefficient between the synthetic and the real seismic data is found or the maximum number of iterations is reached (number of revisits stipulated).

The case study

We can recognize 07 basic steps in the geostatistical inversion:

- Seismic interpretation;
- Log edition;
- Wavelet estimation,
- Structural framework build-up;
- Conventional acoustic inversion;
- variographic analysis,
- geostatistical inversion.

Seismic interpretation

The seismic data available, except for a bottom sea multiple reflection which affects the seismic data in the reservoir level in some places, present good quality.

The reservoir sands show a good acoustic contrast with the background shale. Typically those sands exhibit low impedance values and the amplitude maps taken in the reservoir zone are good indicators of sand presence.

The field reservoirs are Oligo-miocenics turbidites whose deposition was controlled by salt tectonic. A great number of faults cross the reservoirs; some of which controls the sand bodies borders.

According to Bruhn et al statigraphic model for oligo-miocenics reservoirs, several fourth order sequences are defined, which are separated by well-developed condensation zones, an effect of the strong eustatic variation. Such sequences may be subdivided into fifth order sequences, which are not detectable in the seismic data.

In the field under discussion, fourth order sequences, named UN-3 (located between the geological markers Miocen-360 and Oligocen-350) are largely well spread. Above them, more restrictedly, UN-2 (located between the geological markers Miocen-360 and 370) and UN-1 (located between the geological markers Miocen-370 and 380) are also found. The depositional architecture is characterized by confined environments (channels) as well as spills, crevasses and terminal lobes.

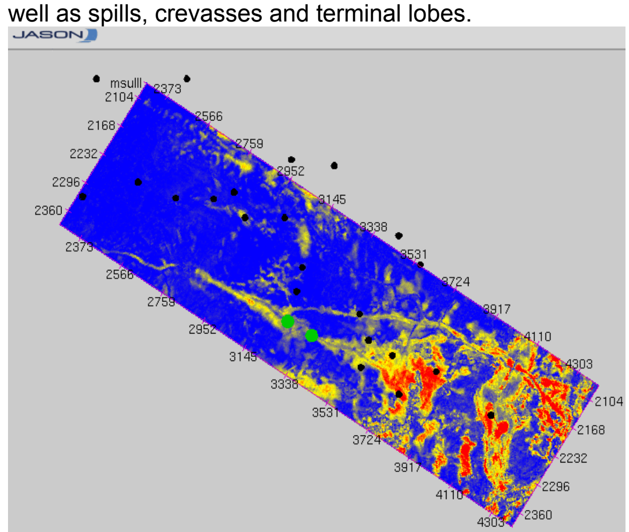

Figure 2 – Minimum impedance map of the interval Miocen-380 and Oligocen-350. This attribute shows depositional main features of the area. P02 and P07 wells are respectively marked by left to right white points.

Log edition

Twenty three wells are taken into account in this study. The sonic and density logs, master keys in inversion methods, may present unreliable values in some parts. These logs may present values which are not correlated to the rock due to interferences such as well collapsing, fluid invasion and so on.

The well log quality control was carried out in two steps. Firstly, *spikes* in the sonic log were removed and the gaps in the density logs were filled by values obtained from a local model from *Gardner et al* equation. Taking then into account core-resistivity log correlations, the extension of the invaded zone was determined. The logs were corrected by the fluid substitution technique (*Gassman* equation).

Wavelet estimation

Wavelet estimation was carried out in two steps. First, a search for each well wavelet which provides the best well-seismic fit is determined. If necessary, the logs are stretched and squeezed. Finally, a global wavelet is estimated by a multi-well algorithm in a way that the best well-seismic fit for each well is provided.

A great similarity in the phase spectrum is observed among the estimated wavelets. However, the same is not true for energy, see Figure 3. P04 well was not considered for the global wavelet since its energy was not compatible with the others, despite the log corrections applied. This well is located close to a fault and probably signal problems and/or processing may have degraded the wavelet.

Structural framework build-up

Three seismic stratigraphic units were defined in the structural framework, taking into account the interpreted horizons (Oligocen, UN-3 and UN-1-2). They exhibit a top parallel internal correlation pattern. The statigraphic correlation lines defined in this step perform the role of spatially guiding the variographic analysis and stochastic simulation algorithms.

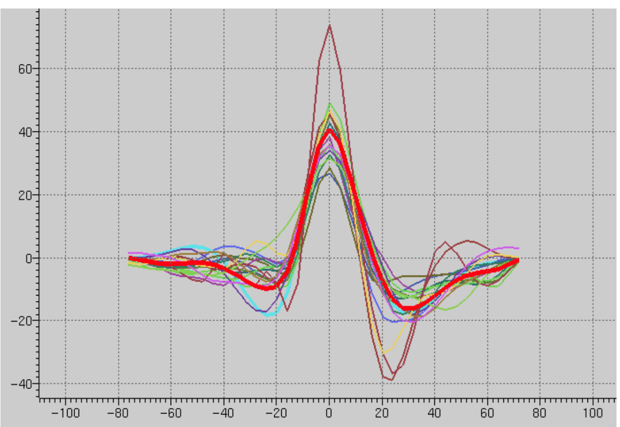

Figure 3: - Field wavelets. The red one is the global wavelet. P04 well was not considered since its energy was too far beyond the others.

Conventional acoustic inversion

A *sparse-spike* algorithm was used to invert the seimic data. In this step, the previously estimated global wavelet was used. In this algorithm, the acoustic impedance background (low frequency) is obtained by the well log impedance interpolation through the correlation lines defined in the structural framework.

Variography

A variographic analysis was performed separately in each unit defined in the structural framework. The well impedance log vertical variogram is easy to model, due to high information density, but the same is not true for horizontal variograms. That may be circumvented by the assumption that sparse spike impedance horizontal variability (highly horizontally sampled) well represents the horizontal wells variability. Table 1 and Figure 4 show the fitted variographic models. The low range nested structures are possibly related to the channelized facies from the turbidite complex.

Table 1 – Fitted variograms

Unit	Model	Range X	Range Y	Range Z	Sill
Oligocen	Spheric	500	500	15	0,3
	Spheric	3500	3500	20	0.7
UN – 3	Spheric	300	300	4	0,43
	Spheric	4500	3000	20	0,57
UN-1-2	Spheric	400	400	4	0,4
	Spheric	3500	1500	20	0,6

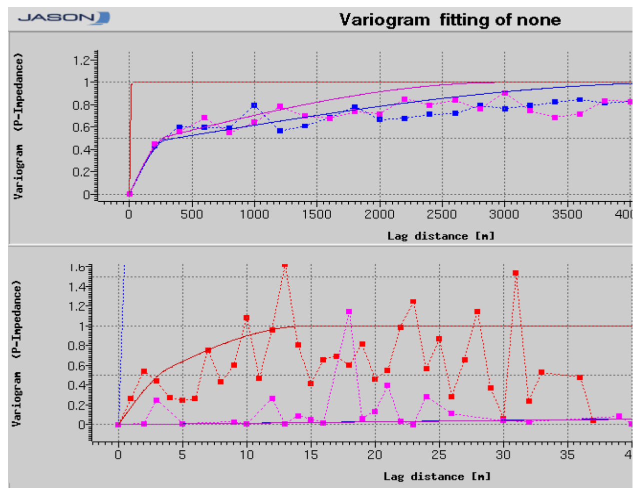

Figure 4 – UN-3 Variograms (top – horizontal/bottom – vertical)

Geostatistical Inversion

The above described algorithm was used to implement the geostatistical inversion. The sparse spike impedance was taken as secondary variable in a *Gaussian collocated cosimulation*. This approach aims at restricting the solution space and increasing the spatial coherence in the simulation process.

Only 10 high resolution acoustic impedance realizations were performed due to its high computational cost. Four additional volumes were calculated: the mean of the realizations, the maximum, the minimum and the standard deviation. Maximum and minimum volume values may be used for optimistic and pessimistic evaluation scenarios. The standard deviation volume feeds quality control and the mean of the realizations constitutes the most reliable seismic scenario.

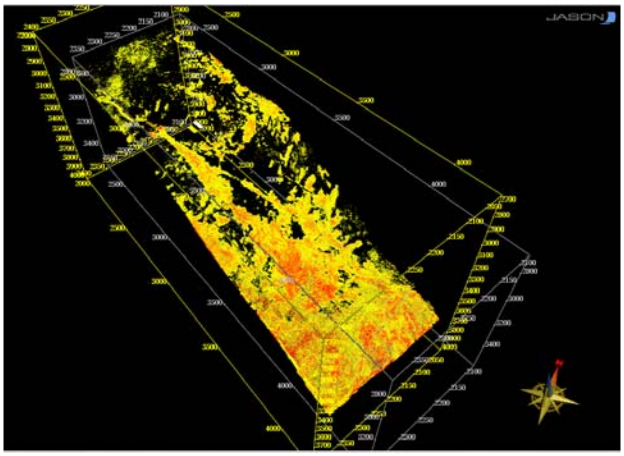

Figure 5 – Average of the 10 realizations of the geoestatistical inversion in the field area**.**

It is well known that the mean of the realization of one stochastic conditional simulation process is equal to the data interpolation by kriging. Naturally the variability (or high frequency) of the stochastic process is lost. But that is not noticed when the mean of the realizations of the stochastic inversion is done, Figure 8, what is due to the fact that the stochastic inversion selection of seismic reliable realizations diminishes the solution space. In other words, the seismic rank of the stochastic realizations generate a biased solution, the mean of which is not equivalent to a kriging interpolation, but it is close to a conventional sparse-spike inversion, showing greater resolution in the neighborhood of the wells.

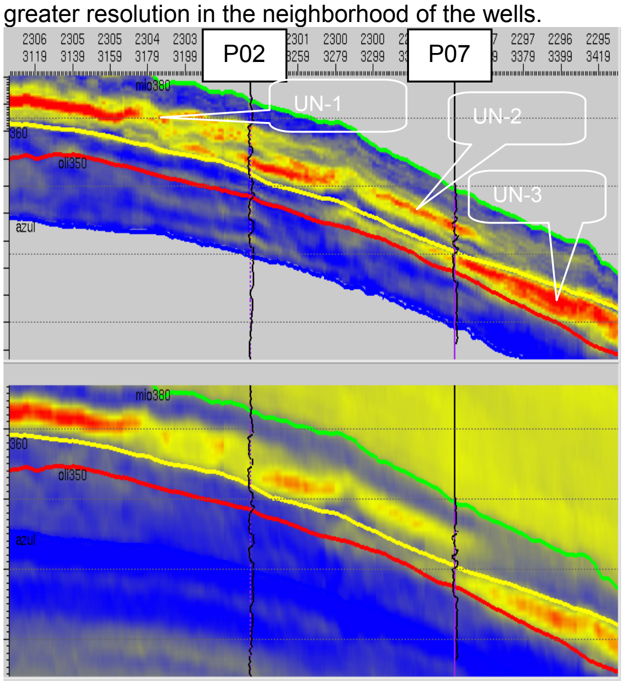

Figure 6 – Compare the resolution improvement obtained by the geostatistical inversion, top section, to the sparse-spike inversion, bottom section. Note the better edge definition of the UN-3 body. Section localization can be seen in Figure 2.

Cross Validation

One cross validation test was done in the neighborhood of P02 and P07 wells. The geostatistical inversion was performed without P02 well. The results, as can be seen in Figures 7 and 8, are very robust. Nevertheless, it is noticed that for P02 well neighborhood, some resolution is lost. However, the results are much closer to the conventional sparse spike inversion. A close observation of Figures 7 and 8 show that, despite the resolution loss, geostatistical inversion was able to separate UN-1 and UN-2 sands in P02 area.

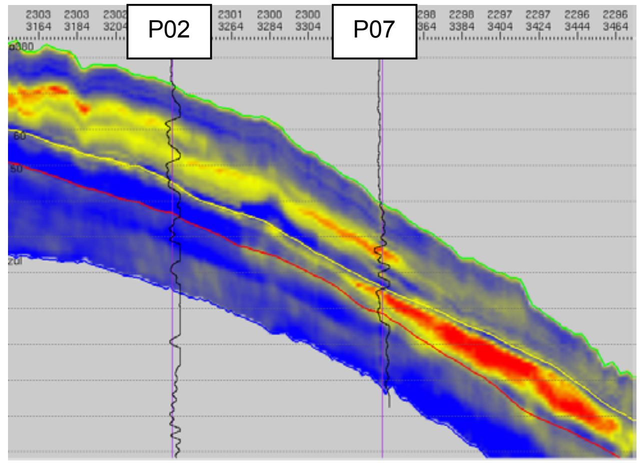

Figure 7 – Cross validation, average of 10 realizations. P02 well was not taken into account during the geostatistical inversion. UN-1 and UN-2 are still discriminated in P02 well neighborhood.

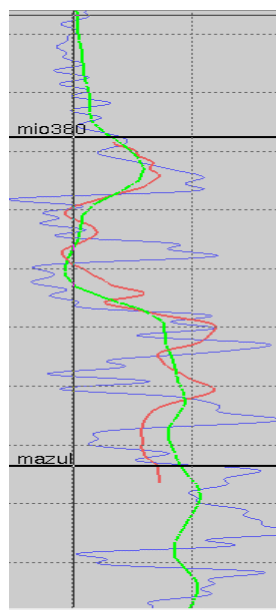

Figure 8 - *B*lind Test P02 well: Real impedance log in blue, the sparse-spike inversion results in green and the mean of the geostatistical inversion realizations in red. This picture shows that geostatistical inversion result is very close to conventional sparse-spike inversion result, although improved in resolution.

The use of geostatistical inversion in reservoir modeling

The support difference between the seismic data and the well data is a great problem to 3D reservoir modeling. Despite the fact that some sophisticated well-seismic data integration have been tested, see Schwedersky Neto et al (2000), the seismic attributes, in its great majority, have been used as average maps in the 3D reservoir modeling.

This is one of the great advantages of the geostatistical inversion. The acoustic impedance obtained by this methodology presents the same support of the wells, since it is the result of a stochastic simulation of a well data. This characteristic allows us to use this impedance as a secondary variable in 3D co estimation systems, filling the reservoir grid with the well properties, improving the model resolution and acquiring greater reliability.

The example in Figure 9 shows that the facies model which used the conventional sparse-spike inversion as a trend variable presents lower resolution than the model in which the mean of the realizations of geostatistical inversion was used in 3D. This model represents more accurately the reservoir heterogeneity and improves the quality of the flow simulation models.

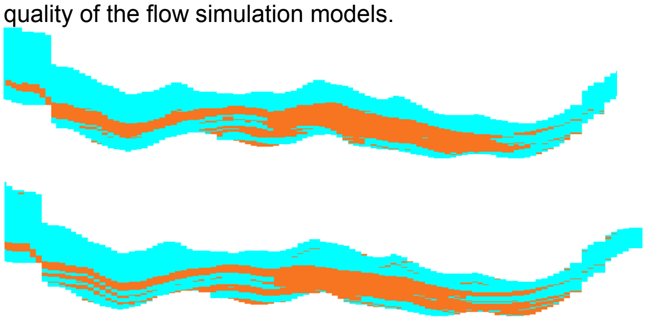

Figure 9 - These facies models were obtained by indicator collocated cokriging. The upper one used, as a secondary varibale, a conventional sparse-spike inversion; the bottom one used the mean of geostatistical inversion realizations. Resolution was gained, as it may be observed.

Final remarks

Geostatistical inversion proves to be a powerful tool for thin beds reservoir modeling.

The methodology here applied, which uses the acoustic impedance obtained by geostatistical inversion as a secondary variable in the co estimation process of the reservoir petrophysical properties, produces good results due to the support compatibility with the well data. The facies models generated show a better description of the reservoir heterogeneity and produces more robust models for flow simulation.

The average of the realizations present results which are very close to the conventional sparse spike inversion. Thus it may be used to pick horizons in a deterministic approach, with the additional advantage of obtaining a resolution gain in the wells vicinity.

All the impedance volumes obtained by geostatistical inversion (a realization of the random variable well impedance) show the same probability of being correct, and could not be used in a deterministic approach. The reservoir limits mapped in one volume may not necessarily be the same mapped in another volume, but the interpreted limit in the raw amplitude seismic or in a conventional inversion is not in the correct position either. The interpretation of some realizations may show itself to be a more appropriate approach to address the reservoir pinch-out problem, since it takes into account the statistical point of view and brings about the necessary uncertainty considerations.

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