Geostatistical Inversion of Prestack Seismic Data

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Abstract This paper presents a method for geostatistical inversion of prestack seismic data to obtain P-wave and S-wave impedances (Ip and Is, respectively) and access the uncertainty of estimates. This is a generalization, to prestack seismic data, of basic principles of geostatistical inversion with a global perturbation method (Soares, Diet, & Guerreiro, 2007). To solve the inversion problem, geostatistical methods of direct sequential simulation and co-simulations are used as perturbation methods, to generate images of impedances in an iterative approach to successful converge to the match of an objective function of the real seismic and synthetic seismogram. The algorithm is implemented using Fatti's equation (Fatti, Smith, Vail, Strauss, & Levitt, 1994), based upon Aki-Richards approximation, thus assuming that the angle-dependent reflectivity is independent of density, which simplifies the problem. To characterize simultaneously the P-impedance and S-impedance, keeping the data relations observed at the wells, a new algorithm based on the method of co-simulation with bi-distributions (Horta & Soares, 2010) is presented. The application of this methodology is illustrated with a synthetic dataset, allowing quantification of the mismatch between inverted Ip and Is and the "real" models. The method can be used to combine Ip and Is models to derive other elastic parameters.

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Introduction

This paper presents a method for geostatistical inversion of prestack seismic data, to obtain the P-wave and S-wave impedances (Ip and Is) models. The physical model relating Ip and Is with seismic amplitude is described by the Zoeppritz equations, which characterizes the transmission and reflection of P and S waves in an interface of different properties media, for different angles of incidence, and for which the Aki and Richards equation is an approximate solution. (Haase, 2004)

Fatti et al., (1994) simplified the Aki-Richards equation to:

$$R(\theta) = \left(1 + \tan^2\theta\right)\frac{\Delta I_p}{2I_p} - 4\left(\frac{I_s}{I_p}\right)^2 \sin^2\theta \frac{\Delta I_s}{2I_s}. \qquad (1)$$

Equation 1 is used to obtain the reflection coefficient from the Ip and Is, as a function of the incidence angle θ, which is valid for small differences between the densities on both sides of the interface, when the relation Ip/Is is approximate to 0.5 and the θ angle is considerably smaller than 90º.

Synthetic amplitudes a(θ) are obtained, for each angle θ, by convolving R(θ) with known wavelets w(θ):

$$a(\theta) = R(\theta) * w(\theta). \qquad (2)$$

The algorithm of Geostatistical Seismic Inversion

The seismic inversion algorithm presented in this paper, is a generalization of acoustic inversion GSI (Soares, Diet and Guerreiro, 2007) to elastic inversion, and is based on following key ideas:

1- The use of sequential direct co-simulation with reproduction of bi-distributions (Ip, Is) as the method of "transforming" 3D images, in an iterative process, with the same spatial pattern.
2- The integration of the sequential procedure of a genetic algorithm optimization to converge the transformed images towards an objective function.
3- Usually Ip and Is are related with simple linear functions. However in presence of more complex (mixture of populations or different litho-groups) relations, the linearity between Ip and Is cannot be considered appropriated. Hence in this paper it is proposed a new method to simultaneously generate and transform the Ip and Is images.

The algorithm can be summarized in the following steps:

- Generating the initial simulations
- Cycle until the desired value of an objective function is achieved:

a) Classification of the realizations of Ip and Is according to an objective function, which measures the match between the synthetic seismograms (created by equation 2) and the real seismic data for each angle θ.

b) Select and recombine the best parts of the simulations Ip and Is in one composed image.

c) Generate the new set of Ip and Is images by using direct sequential co-simulations with bi-distributions, based on experimental data and the composed image of b) as secondary.

Direct Sequential Co-simulation with Joint Probability Distributions for the Joint Transformation of Ip and Is Images

One key issue of the proposed algorithm is the joint global perturbation of Ip and Is images at a given iteration in order the convergence to the objective function is reached. This is performed with a joint transformation of Ip and Is realizations by using a Direct Sequential Co-simulation with Joint Probability Distributions (Horta & Soares, 2010)

The use of this co-simulation with joint probability distributions allows us to reproduce, at all scales, the bi-variate relations between the two variables (Ip and Is in this case).

The methodology of Co-DSS with Joint Probability Distributions can be summarized in the following sequence (Horta & Soares, 2010)

i) After the global bi-distribution is estimated from experimental data, first covariate $I_P(x)$ is simulated using Direct Sequential Simulation. Realizations of $I_P^{(l)}(x)$ reproduce the variogram $\gamma_1(h)$ and marginal cdf $F(I_P(x))$.

ii) Afterwards, $I_S(x)$ is co-simulated: at each location x_0, estimation of the local mean and variance, identified with estimated simple collocated co-kriging and corresponding estimation variance.

iii) Based on previously simulated $I_p^{(l)}(x_0)$, the conditional cdf $F[I_S(x)|I_P(x)= I_p^{(l)}(x_0)]$ is calculated from the bi-distribution $F[I_P(x), I_S(x)]$. Simulated value $I_s^{(l)}(x_0)$ is re-sampled from the conditional cdf $F[I_S(x)|I_P(x)=I_p^{(l)}(x_0)]$ as in the usual Direct Sequential Simulation procedure (Soares, 2001).

The Is values can be sampled from the conditional distribution by several methods, such as defining a priori classes of $F[I_S(x)|I_P(x)= I_p^{(l)}(x_0)]$ or choosing a given number of closest points to the $I_p^{(l)}(x_0)$ value, which avoids abrupt class changes and artifacts. We have chosen an hybrid method: the bihistogram was sampled using the N nearest points to the collocated Ip value; these were divided in classes to allow local histogram average and variance corrections .

This method can use the experimental bihistograms, when sufficient experimental data is available from the wells. Otherwise to characterize the bi-histogram Ip, Is, one can use smoothing algorithms to populate the bihistogram, like the ScatterSmooth program of gsLib (Deutsch & Journel, 1992).

Elastic Inversion Methodology

The general framework of the proposed methodology (illustrated in Figure 1) can be described in the following steps:

i) At each iteration, a set of Ip and Is image pairs are co-simulated with bi-distributions. For each pair, (Ip, Is) reflection coefficients are calculated for each angle interval available.

ii) The reflection coefficient cubes are convolved with the angle dependent wavelets, generating synthetic seismograms, which are compared with the real seismic.

iii) At each location spatial location, it is retained the (Ip, Is) pair that has generated the best synthetic seismic – best correlation coefficients with the real seismic. In the next iteration, the best Ip and Is cubes are used as secondary information for the co-simulation of the Ip and Is pair, using the best correlation cube for local correlations.

    First the Ip values are co-simulated with the best Ip-cube (previous iteration) as secondary. Next the Is values are generated with direct sequential co-simulation with joint probability distributions conditioned to the previously simulated Ip values.

At the end of each iteration, Is and Ip cubes that respect the joint distribution (Ip, Is), as well as the variograms and experimental Ip and Is data, are obtained. Furthermore, the iterative procedure of generating new images based on the best parts of previous iteration guarantees the convergence towards the solution.

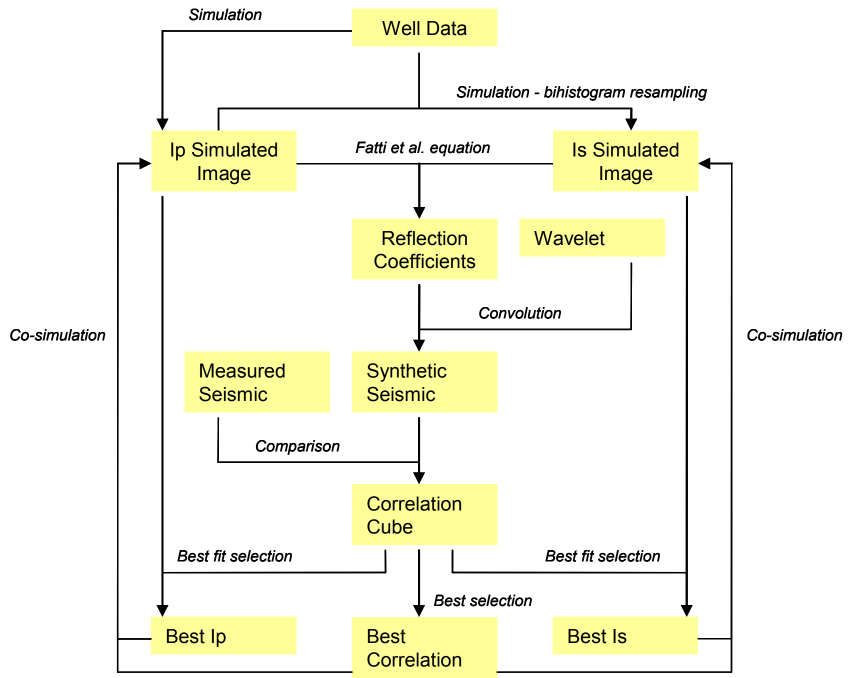

Figure 1 Inversion method

Case Study

To illustrate the proposed methodology, a case study of a synthetic reservoir was chosen. The synthetic dataset comprises seismic data, for four angle intervals; a wavelet for each angle interval; well data, with Ip and Is information; Ip and Is "real" models, for comparison purposes.

Figure 2 shows a cross section of the "real" Ip cube, in which is visible the dark blue low Ip reservoir area. The corresponding cross section for the Is cube is shown in Figure 3.

The final model was generated after six iterations, each having sixteen simulated pairs. Figure 2 has a cross section of the final Ip model, where the similarity with the real Ip area is remarkable. The global correlation coefficient between the two cubes is 0.88.

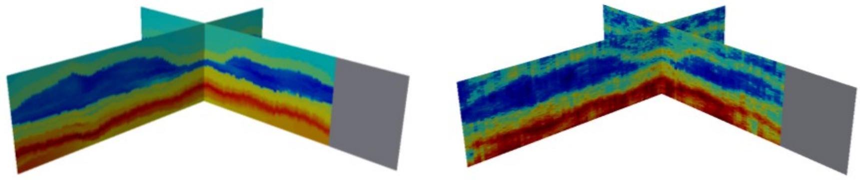

Figure 2 Ip - real, left; best simulation, right

The final Is model is shown on Figure 3. The final model has a correlation with reality of 0.67, and still similarities can be observed.

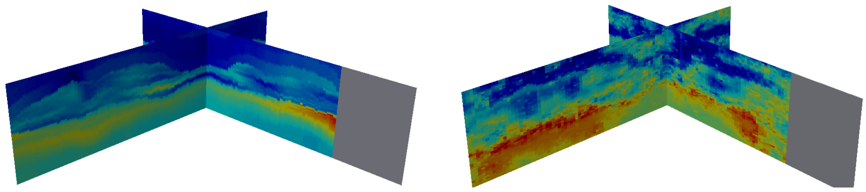

Figure 3 Is - real, left; best simulation, right

The proposed methodology reproduced the bi-histogram of experimental (Ip, Is) data: the bi-histograms are shown in Figure 4

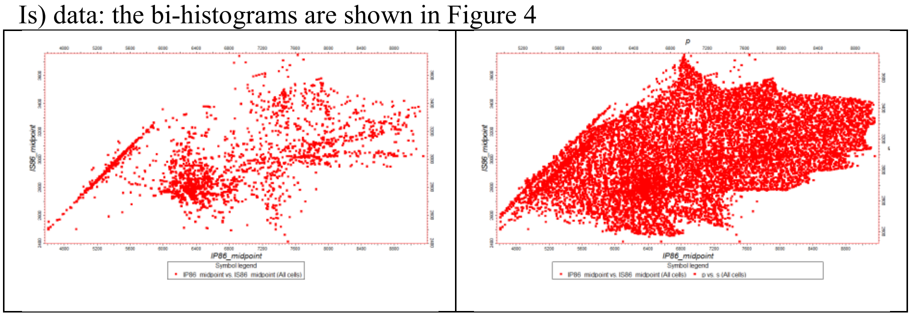

Figure 4 Biplots - observed at wells, left; best simulated pair, right

Final Remarks

A new geostatistical method for the elastic inversion was presented. A joint global perturbation of P-wave and S-wave impedances (Ip and Is) based on the new algorithm of co-simulation with bi-distributions, succeeds to reproduce its bi-distribution. This is a clear advantage of the method to identifying potential reservoir areas.

Although applied in a synthetic case study the method showed very promising results for elastic inversion. Real dataset applications have been done with a very promising results. The algorithm is parallelized, following the same framework of (Nunes & Almeida, 2010), allowing for inversion in useful time.

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