Using Seismic Attributes in Facies Distribution for Reservoir Models

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Abstract

We describe a workflow that was successfully applied on two case studies in the Campos basin, southeast Brazil, to allow (1) the extraction of reliable geological information from multivariate seismic data, and (2) to incorporate this information as a constraint into high-resolution geological models. This paper focuses on the first part of this workflow (extraction of a meaningfull seismic constraint).

Introduction

Modern seismic data contains important information that can be used to build the reservoir model. However, the extraction of meaningful seismic attributes, and their integration to the geological model is not a trivial task. Consequently, whereas in many cases the seismic attributes would be useful to better control of the distribution of heterogeneities inside the geological model, this information is lost in the construction of the final model.

In this paper, we present a methodology to incorporate seismic information in reservoir models, using a wide range of multi-attributes seismic facies analysis techniques. This methodology is demonstrated on two case studies from the Campos basin, deep offshore Brazil, on the Oligo-Miocene reservoirs of the Barracuda and Marlim Sul fields. These fields were chosen because of the availability of seismic elastic inversion results. Previous geological modeling attempts were also available, and used as reference throughout the project.

Advanced Statistical Pattern Recognition

Different statistical techniques were used to manipulate the seismic data. As a first step, Principal Component Analysis (PCA) was used to verify the relationships between the seismic attributes, and thus to reduce the number of independent dimensions in the data set.

Several algorithm were subsequently used to discriminate the data in different classes. These algorithms are mainly based on discriminant analysis. Discriminant analysis is a statistical method of supervised classification. It allows to classify an anonymous point, characterized by the values of a certain number of variables (e.g. principal components), into one of several classes, defined a priori thanks to known points called training samples. As the analysis is done in a probabilistic frame, it allows to associate probabilities to each of the established categories, and therefore provides a powerful control of the quality of the discrimination. The discriminant analysis techniques used in this paper are fully non linear, and involve non parametric probability density function estimation schemes. They can therefore track complex patterns in the attribute space.

Qualitative seismic analysis can be either supervised or unsupervised. In the supervised approach, a priori interpretation of the data is needed. In the unsupervised approach, well information is involved for the a posteriori interpretation of the seismic facies. Using both supervised and unsupervised schemes allowed to produce the best picture of the reservoir, and resulted in a more robust analysis of the seismic facies. In the following, we review into more details each of the techniques applied.

Supervised 2D analysis

In the supervised 2D analysis, attribute maps are calculated for each reservoir window. Each facies will correspond to a particular shape of seismic trace, which will, if possible, be interpreted in terms of geological features. The definition of the form and size of the window is of extreme importance. The window can be defined between two interpreted horizons, or can use a single horizon as base or top for a constant window. Horizons must be carefully chosen, since any problem with the horizon will strongly impact the quality of the results. Another criterion that must be taken into account is the thickness of the window, which should contain only a limited number of seismic events.

For the two case studies used in this project, a constant window above the blue marker (regional stratigraphic marker) was adopted, and the seismic attribute of choice was acoustic impedance. In the Marlim Sul field, the window was 100ms above blue marker, the seismic sampling rate being 4ms. In the Barracuda field, a window of 120ms with the same sampling was used. Once the window defined; the volume was flattened using the blue mark as reference to withdraw the structural effect, and slices were extracted (25 slices for the Marlim Sul data and 31 slices for the Barracuda data). Trial and error proceeding established that the best results were obtained using a 13 slices for each field, covering the Oligo-Miocene reservoir. The 13 slices were then combined into new attributes using PCA. After the PCA, two training samples were constituted using two classifications proposals: (1) thickness and (2) geological environment, based on well data interpretation. The form and discrimination capacity of the typical seismic trace for each class in each scenario was verified, as well as the capacity of separation of the attributes used. Once the validity of the training samples was assessed, discriminant analysis was applied on the full the data sets.

The results for the classification by thickness criteria for the Marlim Sul field were efficient. However, the geological environment classification was initially not very satisfying. It appeared that one of the wells presented a great reservoir thickness, with a trace shape for discrimination that was very different from the others in his class. This well was therefore separated and considered in a class of its own. Based on the analysis of the unsupervised classification (see below), a pseudo well corresponding to an undrilled depositional environment was also added. Those two refinements allowed to greatly improve the quality of the seismic facies map (*Fig 1*).

In the Barracuda field, the result obtained with the depositional environment criteria and two facies (channel and spill) was not conclusive. The obtained seismic facies map looked similar to the one resulting from the unsupervised analysis, but the "spill" was predicted in the central position of the turbidite, and the "channel" on the side, in complete contradiction with what was expected (Fig 2). Classification results based on a reservoir thickness criterion were not more conclusive, and supervised analysis classification results were therefore not used in the subsequent geological model building of the Barracuda field were therefore only the discrimination between reservoir or non-reservoir from the elastic inversion (P and S volumes). This failure is attributed to the smaller number of well available to build the training sample.

Supervised 3D analysis

In the supervised 3D analysis, each seismic sample, or, in other words, each voxel, is given a value of dominant lithology. Multivariate seismic data is necessary to achieve this result. In the present cases elastic inversion results (volumes of P-Impedance and S-Impedance) were used.

As in the 2D approach, the analysis begins with the preparation of a training sample. This step is very important for the understanding of the geological meaning of the generated facies cubes. The training sample is prepared using the lithology and P and S impedance well logs, after application of an appropriate pre-processing workflow. The quantitative logs (P and S impedance) are first converted to time, and then filtered with a high-cut filter in the seismic bandwidth (in the present cases 80-110Hz), before being finally resampled at the seismic sampling rate of 4ms.

The facies logs undergo a different upscaling process. After conversion in the time domain, the proportion of each lithology is computed in a sliding window. The size of the window is tuned according to the seismic resolution (i.e. the seismic frequency content). The dominant lithology is then set to the value of the lithology having the highest proportion in the window. Finally, the upscaled facies log is also resampled at 4 ms.

Cross-plotting between P-Impedance and S-Impedance data allows to visualize the sample groups, at both well and seismic scales, in terms of facies repartition (Fig 3). Two studies were carried out. In a first attempt, a classification in two lithologies (reservoir and non-reservoir) was used. In an effort to improve this simple classification, a new eletrofacies study involving a more precise description of the reservoir in two lithofacies was carried out. This new study attempted to use the core description to classify the samples according the depositional environment. It appeared however that this refined classification was difficult to achieve, even using well logs, due to the characteristics of the sandstones composing the reservoir. Unsurprisingly, the available seismic attributes and resolution were not able to discriminate the reservoirs into more than one class, and the three facies case was therefore abandoned.

For the two fields the percentage of correct assignment of the two retained dominant lithologies (reservoir and non reservoir) was greater than 90% (Fig 4). This value represents the theoretical capacity of the seismic attributes (P and S impedance) to discriminate between the two a priori classes of the training sample. A 90% value is very good, and authorized the use of discriminant analysis to predict a dominant lithology on the whole field.

Along with the dominant lithology volume, discriminant analysis predicted an associated probability volume, used for quality control purposes. These volumes were divided in three units, and proportion maps of reservoir facies were calculated for each of these units (Fig 5).

Non-supervised analysis

Non supervised analysis allows an open vision of the interpretation, unbiased by any a priori about the data. Unsupervised seismic facies maps confirmed the results obtained in the supervised analysis approach, particularly in the case of seismic facies related to depositional environments (channel, spill, lobes, etc.). Unsupervised analysis was also used to complement supervised analysis as it appeared on unsupervised maps that some relevant stratigraphic features were not sampled by well data. Those regions were added as new geological environments in the supervised analysis, to refine the supervised facies maps. This is a good example of the complementarity of the two approaches.

Conclusions

The project allowed to draw the following conclusions:

- 3D supervised analysis was very successful in terms of reservoir/non-reservoir prediction. A reliable dominant lithology cube was obtained for each field, with an associated probability volume used for quality control. Lithology proportion maps were derived from these volumes, and used to constrain static geological model simulations.

- Those results were however limited, in a certain way, by the characteristics of the reservoir rocks under scrutiny. Even using well logs, separation of reservoir rocks into several lithological classes was very difficult. 3D seismic facies analysis was therefore limited to a description of the field in terms of reservoir occurrence only, and was not able to predict directly reservoir quality
- This limitation was partly overcome by the use of 2D seismic facies analysis, both supervised and unsupervised, which allowed to delineate areas associated to different depositional environment. The seismic facies maps interpreted in terms of depositional environments were also directly used in the static geological model building.
- From a methological point of view, the project emphasized the complementarity of supervised and unsupervised approaches in seismic reservoir characterization. Used together, those techniques allow an unbiased and easily interpretable description of the reservoirs, that can be used directly to constrain static models simulations.

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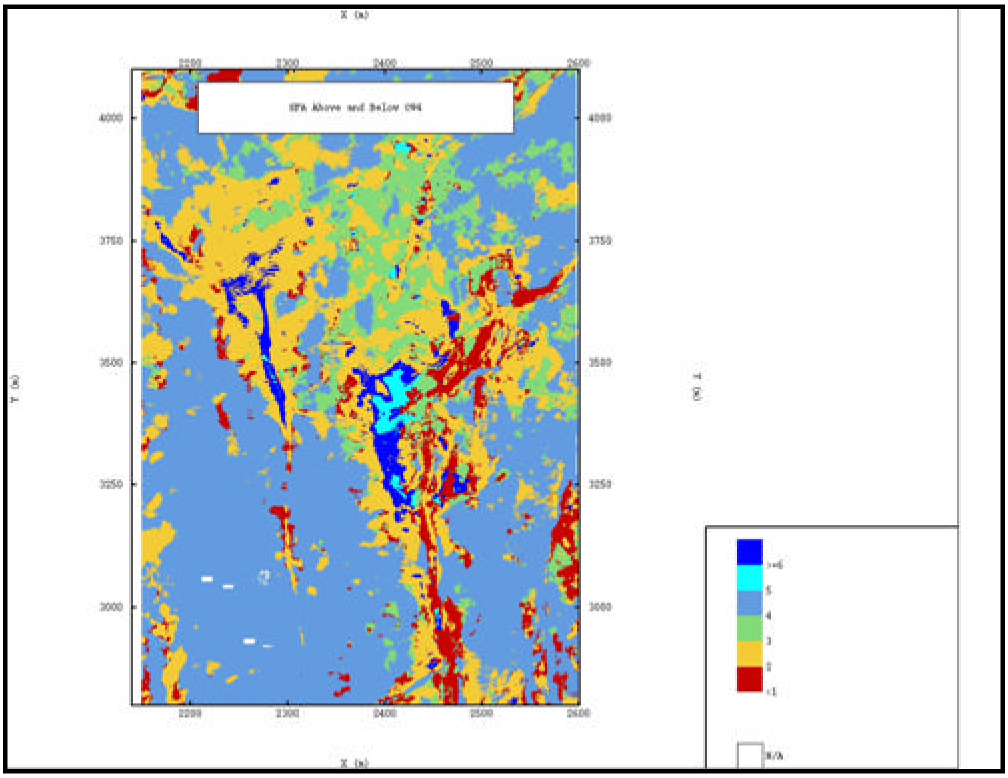


Figure 1: Sismofacies map for Marlim Sul field: (1) channel; (2) lobe; (3) spill; (4) non-reservoir; (5) Well A (thick lobe) and (6) pseudo well (channel in upper reservoir).

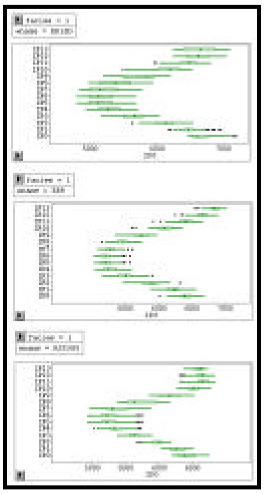
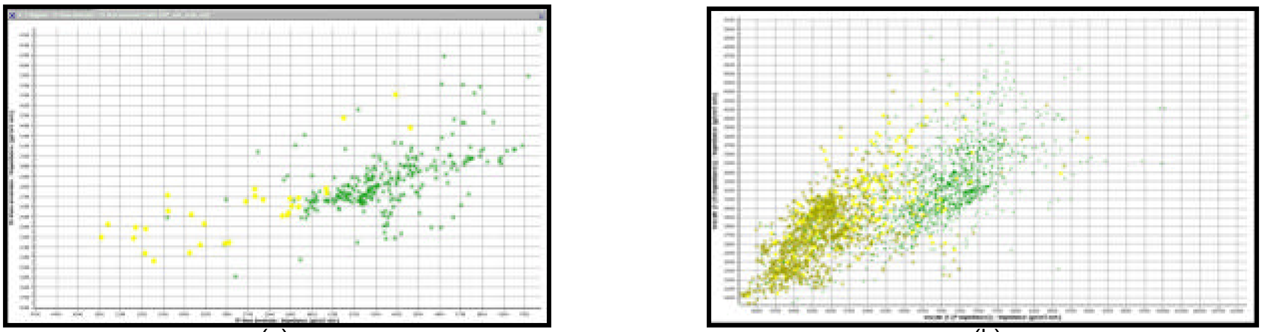
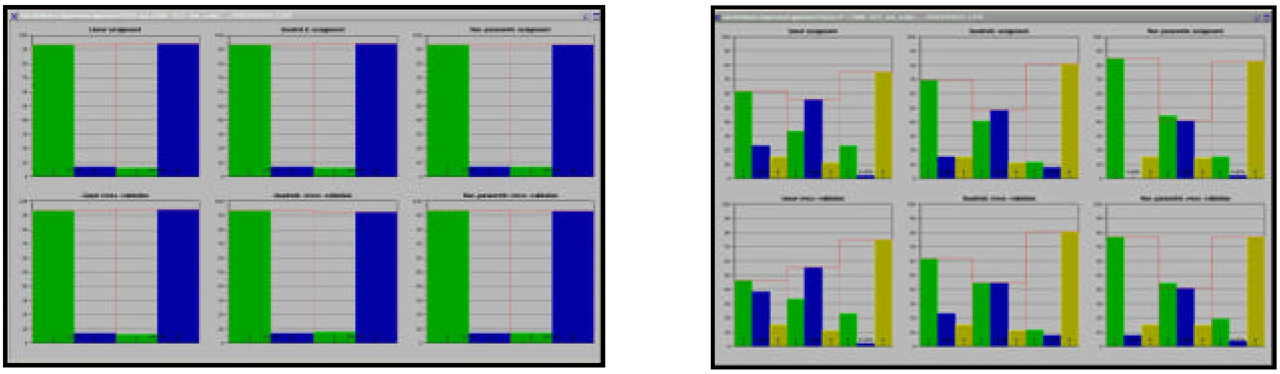


Figure 2: Training samples used for Spill facies in Barracuda field. The last well does not fit very well (a little difference in shape form) so it was used in a blind-test. Later it was identified some doubts for his classification.



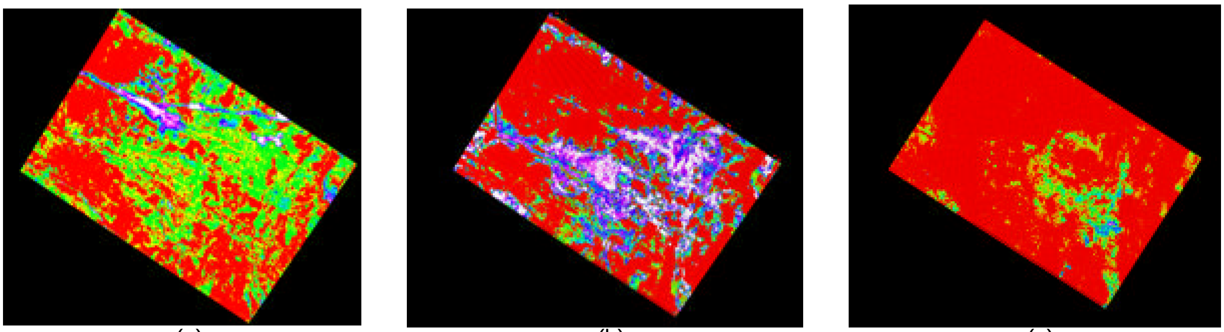
(a) (b)

Figure 3: Crossplots examples for P and S impedance; (a) for Barracuda field in seismic scale and (b) for Marlim Sul field in well scale. For the two facies case (a), with reservoir (yellow) and non-reservoir (green), was achieved a very good correlation. However, the three facies case, with two reservoir facies (yellow and dark yellow) and non-reservoir (green), the types of reservoir cold not be discriminated.



(a) (b)

Figure 4: Results for the 3D supervised analysis for two facies (a) and three facies (b). For two facies case was achieved a 93% of correlation for Facies 1 and 94% for Facies 2. In the three facies case, only the non-reservoir achieved more than 80% values.



(a) (b) (c)

Figure 5: Proportional facies maps for Marlim Sul reservoir: (a) upper; (b) m iddle and (c) lower reservoir.

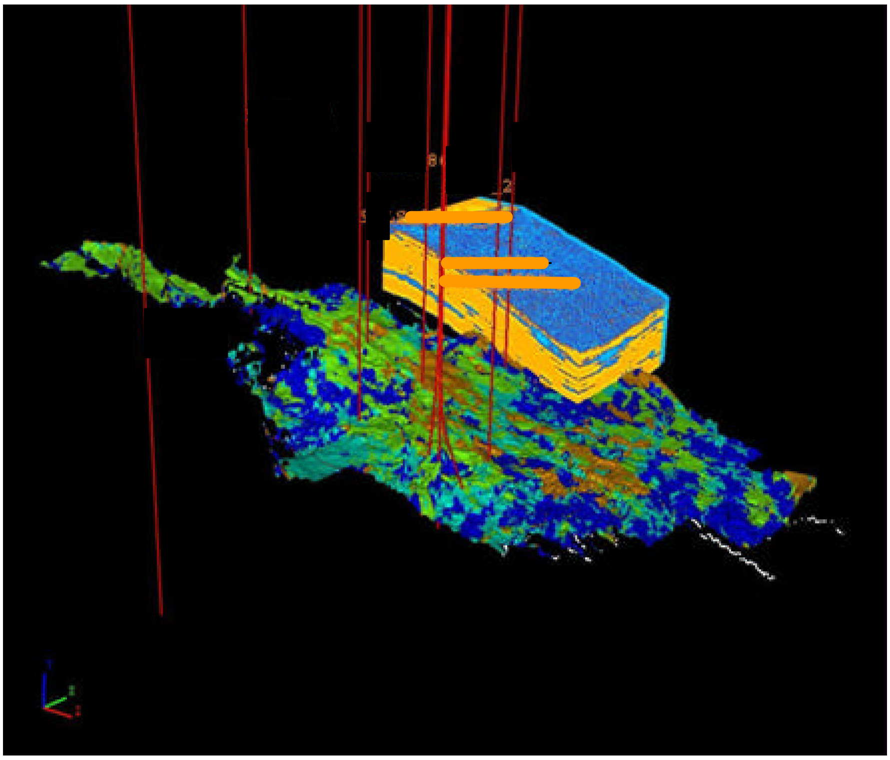


Figure 6: Facies volume (reservoir in blue) and top reservoir in 2D superposed.