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Multivariate seismic pattern recognition and Kohonen maps applied a deepwater turbidite reservoir in Campos Basin, Brazil

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Abstract

Usually, seismic data is used in a *qualitative approach* to detect changes in the waveform and to pick acoustic continuity of a peak and/or a through. The seismic interpretation is a qualitative inversion procedure for building a model. Today, many works try to use the seismic information in a *quantitative approach*. *Quantitative modeling* could be deterministic and/or probabilistic. We use, in many steps of a seismic processing sequence, examples of quantitative deterministic modeling like seismic migration, some seismic inversion methodology, etc. Probabilistic modeling can be gathered in two groups: multivariate statistics and geostatistics approaches. Close to probabilistic modeling, we have also the neural network method. In this paper, we focus on the application of statistical nonparametric multivariate analysis and neural network modeling for seismic pattern recognition (*seismic facies analysis*) applied a deepwater turbidite reservoir from Campos Basin, Brazil.

Principles of the methodologies

The *statistical nonparametric multivariate seismic pattern recognition* is carried out in four steps (Johann, 1997):

1) Definition of the space of analysis (sample or input space),
2) Clustering sample data for the generation of training data set. Two different approaches could be used to carry out this stage:
   a) The nonparametric density estimation or *unsupervised approach,*
   b) The definition of a learning data set or *supervised approach.*
3) Classification of the sample space from the training data set with a nonparametric discrimination analysis,
4) Interpretation of seismic facies maps.

The *unsupervised approach* will extract the main statistically common characteristic underlying in the seismic traces segments at each seismic stratigraphic unit. The *supervised approach* will use the stratigraphic knowledge to guide the pattern recognition (Dumay and Fournier, 1988).

The first important step is to built a learning data set (Fig. 1). It could be is carried out by applying in two approaches: non-parametric density estimation (*unsupervised approach*) or by introducing stratigraphic knowledge (nearest seismic traces from a groups of wells, *supervised approach*).

In the *unsupervised approach,* we need to estimate the statistical number of class underlying in the input space for each seismic stratigraphic unit that we would like to analyse. We can use this information to introducuce the Kohonen methodology, which is the second method described in this paper.

The second main feature is the nonparametric multidimensional discriminant analysis (step 3), which is carried out in two steps: (1) The validation of the choice of the input space and the extraction, among all the available variables, those that are discriminating the best the variability of the variable; (2) The classication and automatic mapping of all seismic traces segments at each seismic stratigraphic unit from the pattterns of the training data set. We can use the discriminant analysis to classify the features of maps generated from the Kohonen methodology, which will represent the second possible link between both methodologies.

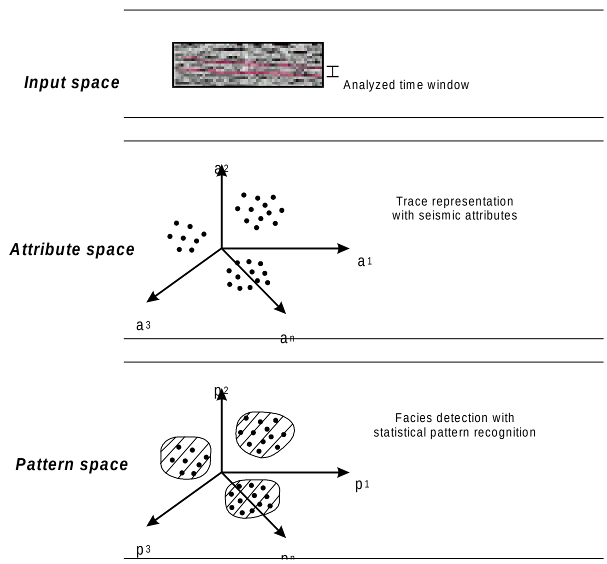

Figure 1. Flowchart of seismic pattern recognition methodology (*seismic facies*): 1) Definition of the input space (seismic traces segments from a target window), 2) Clustering the input samples for generating a training data set, 3) Classifying sample space from the training data set with a nonparametric discrimination analysis.

The *Kohonen map methodology* is a self-organizing feature mapping (SOFM) based on neural network methodology (Kohonen, 1982a). It has been adapted to be applied on seismic pattern recognition by Elf Aquitaine (Morice et. al., 1996) and implemented in Stratamagic, software available for petroleum industry, by CGG-Petrosystems.

The main steps of the Kohonen neural network methodology applied for seismic pattern recognition are:

1) Sampling the data set of interest to create an input space (seismic morphology from a target window).
2) Specify a number of classes in order to create a synthetic model of traces which will represent the variability of the seismic trace morphology over the input space or learning data set.
3) Specifying a number of iterations (building the different levels of topography maps).
4) Automatic creation of the model over the learning data set and generation of a correlation coefficient for all seismic traces within same target window (defining a regional space for searches over the input space).
5) Classify all seismic traces from the raw seismic block at the target window to produce a seismic facies map for the interval of interest.
6) Interpretation of seismic facies maps.

The Kohonen neural network method is a *competitive learning* process where the output neurons of a neural network compete among themselves for being the one to be *active* (or *fired*). Only a single output neuron is active at any time. This hereabove feature will make the competitive learning process highly suited to extract those statistically salient features that will be used as a reference, in order to classify a set of input patterns.

This neural network method has an additional level of organization. When nodes, which are physically adjacent in the network, encode patterns that area adjacent in the input pattern space. The concept of proximity leads to the idea of a *topography* or *map* defined over a neural layer in which these maps represent some feature of the input space (Fig. 2a).

The network architecture consists of a set of inputs (e.g., seismic traces) that are fully connected to the self-organizing layer, but without lateral connections. The important principle for map creation is that training should take place over an extended region of the network centered on the maximally active node (Fig. 2b). The concept of neighborhood is required for the net. This may be fixed by spatial relation between nodes within the self-organizing layer. However, learning takes place over an extended neighborhood. Consequently, the regional trend will initiate a map formation.

The *competitive learning process* will use the ability of network to learn from its environment, and to improve its performance through iterative learning process of adjustments applied to its synaptic weights and thresholds. Consequently, the Kohonen neural network will extract *clusters* of similar patterns in the data without supervision. The learning process involved in the computation of a feature map is stochastic in nature, which means that accuracy of the map depends on the number of iterations (Fig. 2c) of the SOFM algorithm (Lippmann, 1987 and Haykin, 1994).

The main objective is to decrease the size of the neighborhood over the first phase of the process (Fig. 2b), for the creation of the *topography map*. It will imply the process to take into account best-matched nodes and will introduce only small adjustments to map for thinner variations of the input space.

There are three basic steps involved in the application of the Kohonen algorithm: sampling, similarity matching, and updating. The spatial location of an output neuron in the topographic map corresponds to a particular domain or feature of the input data (Kohonen, 1990a).

The *classification process* is a main important step of Kohonen network applied to seismic pattern recognition, after the definition of the model of synthetic traces, which represents the different identified clusters. Class labels may be attached to nodes. However, nodes may become classifiers by presenting patterns to the net, finding the responding node of maximum correlation and labeling it according to the class of that pattern. We can use hybrid approach to classify input space with a combination of the feature map and a supervised linear or nonparametric classifier.

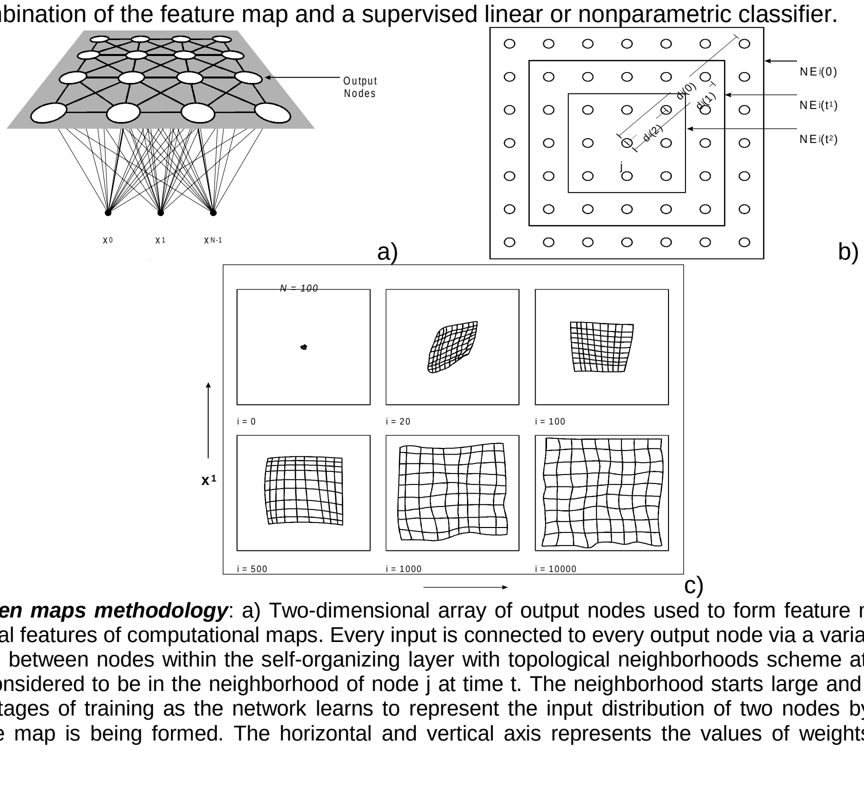

Figure 2. ***Kohonen maps methodology***: a) Two-dimensional array of output nodes used to form feature maps. The model tries to capture the essential features of computational maps. Every input is connected to every output node via a variable connection weight; b) The spatial relation between nodes within the self-organizing layer with topological neighborhoods scheme at different times. NEj(t) is the set of nodes considered to be in the neighborhood of node j at time t. The neighborhood starts large and slowly decreases in size over time; c) Six stages of training as the network learns to represent the input distribution of two nodes by weights to 100 outputs nodes as a feature map is being formed. The horizontal and vertical axis represents the values of weights from input Xo and X1,

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respectively (Lippmann, 1987).

Application in a deepwater turbidite reservoir

A target-oriented statistical nonparametric multivariate pattern recognition methodology is applied to a 3-D seismic data for a detailed seismic stratigraphic unit from a Oligocene turbidite reservoir in Campos basin. The *unsupervised* and *supervised* methods have been applied for pattern recognition on an acoustic impedance seismic volume.

The deepwater turbidite reservoir mencioned is cut by a Lower Oligocene canyon and the stratigraphic framework is characterize by sandstones interbedded by shales and marls in different vertical stacking positions.

In terms of acoustic behavior, the morphology of seismic traces shows variability along the reservoir, typical from a turbidite seismic response. On the seismic data set, we have resolution to interpret the top and the bottom of Lower Oligocene reservoir, which will define the external geometry of the turbidites lobes, faults and the Lower Oligocene canyon. In this *qualitative phase,* we observe a variation of the seismic amplitude along the reservoir top and and/or bottom reflectors and that the wiggle shape (wave character) is changing along and between reservoir limits.

To improve the seismic interpretation, the main challenges are to detect automatically and fast the different changes in the waveform (seismic character) and, interpret and link these morphologies (seismic facies) with lito-stratigraphical and/or petrophysical behavior of the reservoir.

To address this challenge over a deepwater reservoir in Campos basin, we apply both the methodologies presented hereabove: (1) *statistical nonparametric multivariate seismic pattern recognition*; and (2) Kohonen neural network maps.

The seismic attributes used for theses analyses are divided in two groups of different seismic processing sequences: (1) DMO/pos-stack/seismic geoinversion (amplitudes, acoustic impedance and reflectivity); and (2) pre-stack time migration/seismic recursive inversion (near-offset, far-offset amplitudes and acoustic impedance).

With the statistical nonparametric multivariate automatic pattern recognition methodology and selecting the attribute acoustic impedance after seismic geoinversion, we have identified **five clusters** (*seismic facies unsupervised approach*) for stratigraphic unit of the Lower Oligocene reservoir. In the *supervised approach,* the wells were regrouped also in five classes. In this approach, the seismic traces segments nearest the wells were used for building the learning data set.

Comparison of results

For analyse both methodologies, statistical unsupervised and Kohonen, we use the same seismic attribute, acoustic impedance, a same number of classes, five facies, and a same window of 40 ms to build the seismic facies maps. In order to find a possible relation between each class of both methodologies, the first step was to map each seismic facies as show in figures 3a to 3e. We observe that the first three classes issued from the Kohonen methodology are representing the reservoir boundaries (turbidites lobes) controlled by well logs with a higher content of porous sandstones. The equivalent area was enterely captured by the first class in the statistical unsupervised approach. As the Kohonen method will minimize the differences between each trace of synthetic model, the result for each class will be a seismic facies map, showing a strong link with the previous and the next class. We are able, inside the turbidites lobes, to observe a degradation of the seismic signal associated with clear sandstones. The fourth class of Kohonen methodology is equivalent to the fourth class of statistical methodology and can be interpreted like high variability traces in marginal areas. The fifth class, for both methodologies, represents the background area dominant by shales. The figure 3f shows the complet seismic facies maps from both methods.

From this study, the major difference between the statistical and Kohonen methods is that the classes, in the second method, are presenting a very close morphology. The first morphology, extracted by the process, will evolve progressively and will represents a spatial distribution around the present class. The principle of the Kohonen method is to use an unsupervised process to map a controlled evolution of the seismic data, using the neural network technology. In the statistical methodology the seismic morphology associated to faults pattern was identified in a class with acoustic behavior different from others facies (Fig. 3b).

Conclusions

The successful application of the two methodologies for 3-D seismic pattern recognition helps us to characterize the external and internal reservoir architecture, by the identification of different morphologies of wave shape, inside the 3-D seismic data set. The methodology of seismic pattern recognition is quantitative, multivariable and automatic.

The Kohonen map is a neural network adequate for geosciences data to provide a spatial analysis of acoustic features, seismic facies. These facies can be interpreted in terms of sedimentological environments, stratigraphical context and average petrophysical properties.

The results over a deepwater Lower Oligocene turbidite field in Campos basin are showing that this type of analysis, is an interesting integrated seismic lithostratigraphic interpretation tool and could be applied for other turbidites fields.

Acknowledgements

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References cited

Johann, P., 1997, *Inversion sismo-stratigraphique et simulations stochastiques: réservoir turbiditique, offshore du Brésil. Intégration géologique, géophysique et géostatistique en 3-D*, Ph.D. Thesis, Université de Paris VI.

Dumay, J., F. Fournier, 1988, *Multivariate statistical analyses applied to seismic facies recognition*, Geoph., 53, n. 9.

Gurney, 1997, An introduction to Neural Networks, UCL Press.

Haykin, S., 1994, *Neural Networks: A Comprehensive Foundation*, Prentice Hall.

Kohonen, 1990a, *The self-organizing map*, Proceedings of the IEEE **78**, 1464-1480.

Kohonen, 1982a, *Self-organized formation of topologically correct feature maps*, IEEE **78 Proceedings**, 1464-1480.

Lippmann, R. P., 1987, *An introduction to computing with neural nets*. *IEEE ASSP Magazine*, 4-22.

Morice, M., Keskes, N., JeanJean, F., Manual and automatic seismic facies on SISMAGE worstation: Na example of image analysis technique applied to the exploration of perdana-Nakhoda turbidic fan complex (Pliocene offshore Brunei), IMA3G research project, Elf aquitaine production. 1996 SEG Meeting abstracts.

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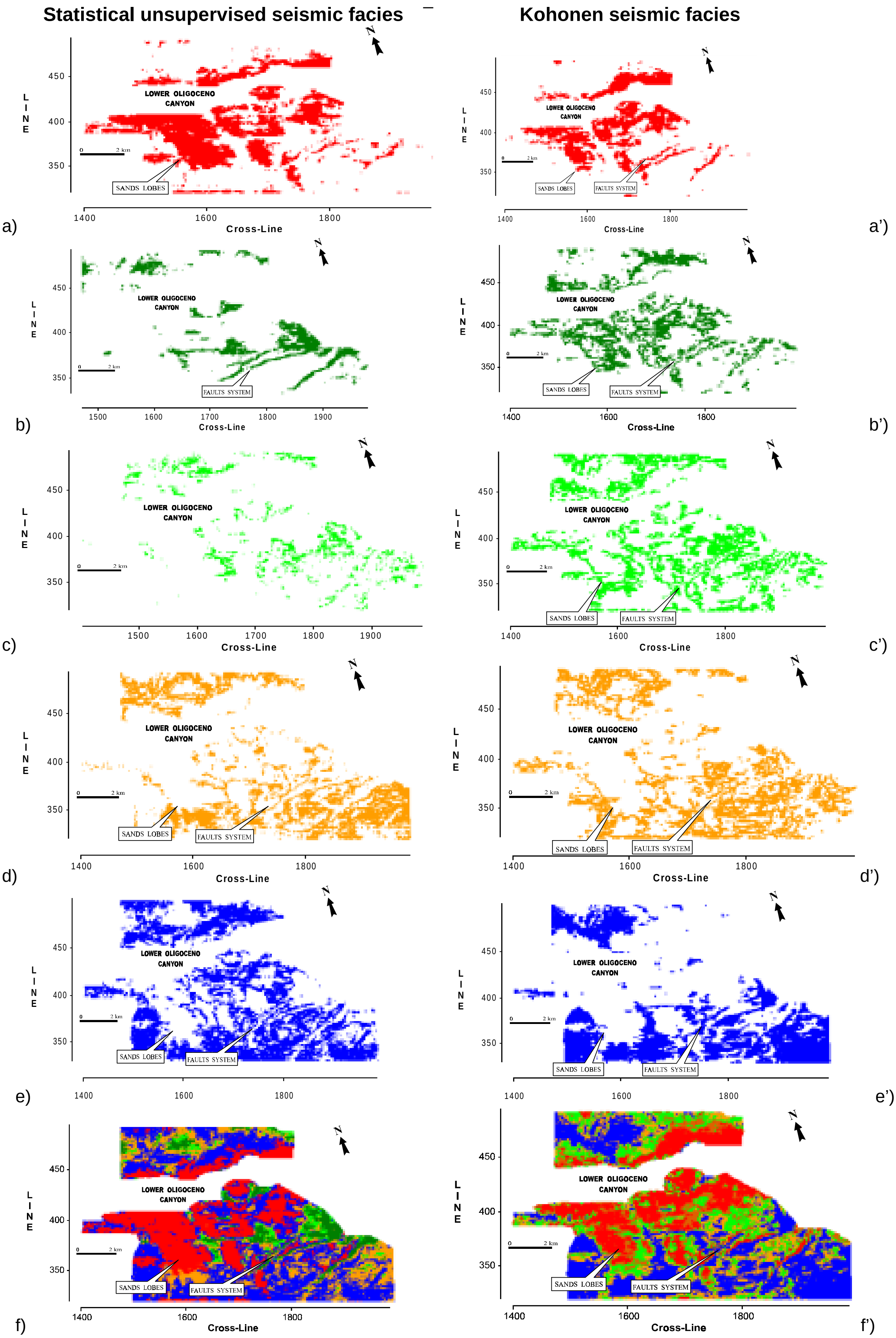

Figure 3. Maps on the left side represent seismic facies 1(a) to 5(e) and total(f) from statistical methodology; Maps on the right side represent seismic facies 1(a') to 5(e') and total(f') from Kohonen methodology.