SUMMARY

Automatic seismic facies classification is now common practice in the oil and gas industry. Unfortunately unsupervised seismic classification is often not optimal. The main criticism of unsupervised classification is the a priori nature of the seismic data set organization and the poor description of seismic due to data redundancy. Data reduction, such as Principal Component Analysis (PCA) is often used in association to reveal the principal characteristics of the geological system. The new clustering described here will with a dynamic process naturally search to fill the data space, and to describe the full variability of the seismic. The process can be imagined as a gas expanding in volume. Finally, the process details the anomalies which potentially correspond to hydrocarbon accumulations.

INTRODUCTION

The major drawback of classification methods such as Self-Organizing Maps (SOM), K-Means, is the strong a priori nature of the data set organization. Indeed, in its basic form, the SOM has a fixed topology and a predefined number of neurons used to approximate the seismic data set. Such hard constrains could be problematic when interpreting an unknown data set. Seismic data are mostly composed of non-reservoir areas. Being able to detect anomalies that could be potentially attractive for reserve accumulation and recovery is challenging. Seismic classification is often associated to PCA to remove noise and filter non reservoir seismic responses. The new neuronal network described below will dynamically fill data space and detect anomalies. The new approach has been applied to pre-stack seismic to detect potential AVA anomalies.

METHODOLOGY

In this section, we describe the Self-Growing Neural Network (SGNN) that gives a graph following the topology of data. Then we explain the clustering algorithm built on this technique and outlier detection.

Self-Growing Neural Network

Self-Growing Neural Network (SGNN) is an unsupervised incremental clustering algorithm, also referenced in literature as Growing Neural Gas (Fritzke, 1996). This technique builds a topology defined dynamically by defining a projection of the data space onto a map with a smaller dimension that keeps neighborhood relationships. This projection respects two criteria: i) two neighborhood data elements in data space must be neighbors in topology space, ii) dense regions of data space must be assigned to several neurons. Contrarily to the SOM, this technique generates topological structures with varying dimensions from one region to another (Figure 1).

Figure 1: Projection of network topology on a disk during the learning process. (A) Neuron 195 will be eliminated from the network as it does not have any connection to other neurons. (B) The main network maintains edges between neurons. The edges evolve during the iterations. All the neurons do not have the same number of topological neighbors. (C) The network is already separated into two sub-networks: one massive in the center of the picture and one linear satellite on the left.

The training of such a neural network is still faced with the drawback of populating high density data zones with most of the neurons. However the unconstrained topology of dynamically growing networks gives strong chances to detect anomalies even if there are not many in the studied area. For this purpose, the introduction of an outlier detection process in the training phase gives the network the capability to populate outlier zones. This process is controlled using outlier detection techniques (Tuckey, 1977).

The number of neurons created during the learning process is generally high. The trained neurons are then agglomerated into classes using a hierarchical clustering algorithm for the sake of simplicity.
Classification

This process defines classes based on distance criteria between neurons. Those classes are propagated to the area of interest by using a weighted K Nearest Neighbors (WKNN) rule. The WKNN is a local version of the Probabilistic Neural Network (Specht, 1990) which computes a posteriori probabilities of class assignments. Let us note $n_c$ the number of neurons of class $c$ within the $k$-size neighborhood. Then the a posteriori probability that $y$ belongs to $c$ is defined as the quantity:

$$P(c|y) = \frac{1}{n_c k} \frac{\sum_{c,k}^{n_c} e^{-\frac{|y-x_{ck}|^2}{2\sigma^2}}}{\sum_{c,k}^{n_c} e^{-\frac{|y-x_{ck}|^2}{2\sigma^2}}}$$

where $x_{ck}$ is the i-th nearest training sample of class $c$ to $y$ and $K$ is the number of classes.

SGNN RESULTS ON THE TARANAKI BASIN

Basin description

The Taranaki petroleum sedimentary basin is located along the west coast of New Zealand’s North Island. The Cretaceous and Tertiary sedimentation occurred in response to the break-up of the paleo-Pacific Godwana margin. The basin is separated into two tectonic areas, the Western Stable Platform and the Eastern Mobile Belt. Currently the main oil and gas fields in production of the Taranaki Basin are located onshore. The area of interest is an offshore exploration area covered by the Parihaka 3D survey (Figure 2) where a set of 3D PSTM seismic cubes and prestack offset collections are available.

Wells description and lithologies

The result of the seismic facies determination by SGNN has to be calibrated at wells to verify its consistency. Consequently, a lithofacies group has been described in detail for offshore wells. The methodology consists in analyzing wireline logs, drill cuttings samplings with respect to side well cores when available. Wells are offshore vertical exploration wells with as primary objectives the late to early Miocene. Mangaa turbidite sands are dated from late Miocene to early Pliocene.
Anomaly detection using dynamic Neural Networks, classification of prestack data

Information. These electro-facies have been computed using a Multi-Resolution Graph Clustering (MRGC). The study ended up with 16 lithofacies groups. They have been sorted from non-reservoir to silicoclastic then volcanoclastic deposits.

Reservoir characterization using SGNN

Pre-stack seismic interpretation has been successfully applied in the previous years. The variation of amplitude with offset is mainly depending on the changes in the angle of incidence, impedance contrast and Poisson ratio (Hilterman, 2001). Therefore, the amplitude variation analysis should help in estimating lithology and fluid content. Unfortunately, the processing sequence is never optimal and introduces additional uncertainties in the final amplitude character. Castagna and Swan (1997) provided a reservoir classification based on the amplitude character as a function of offset. The following four classes have been proposed for the behavior of the top of the reservoir unit:

Class I: strong positive amplitude dimming with offset but staying positive
Class II: Small positive amplitude dimming with offset and potentially transformed into negative amplitude
Class III: Negative amplitude that becomes more negative with offset
Class IV: Negative amplitude that becomes less negative with offset

The quality control of the SGNN results has been done on the southern part of the Northern Graben area where one exploration well has calibrated some units. This area is almost completely covered by a thick Plio-Pleistocene prograding mud-dominated wedge. Below, from latest Miocene to early Pliocene, the Ariki formation consists of a condensed interval of marl deposits. The underlying late Miocene deep-water sandstones of the Mangaa formation are interpreted as turbidite sands in the Northern Graben. Individual sandstone beds are up to 20 m thick.

The well data shows that the sandy Miocene turbidites have lower acoustic impedance than the encasing formations and should potentially be class II, class III or class IV. The upper part of the Mangaa formation shows amplitude brightening compared to the lower part. This is the consequence of two phenomena. First, the upper part has separated individual sandy unit which strongly contrast with interbedded marly-claystone units. The lower part shows more complex stacked sandy units interbedded by shale. Second, there is an important change in the impedance of the sand with depth, the upper part showing a bigger impedance contrast with the encasing formation.

A good acoustic seismic to well tie has been performed: the tie between acoustic synthetic seismogram and the near angle cube is of excellent quality for the Miocene.

The pre-stack normal move out corrected offset collection has been converted to angle-of-incidence domain (AVA). This was done by applying simple 1D ray-tracing using Snell’s law and interval velocities from the smoothed normal moveout velocities. The classification cube from pre-stack angle collection shows a good discrimination of the AVA response distributed to different classes. The most populated class corresponds to the background trend. After being calibrated by the well it corresponds to mud dominated interval with low contrast and no AVA effect. Other classes are quite singular and reflect specific deposits. The cross-section in Figure 4 shows a good discrimination of the condensed Ariki marly unit (in red) which draped the Miocene turbidite sequence. The Miocene turbidites which have relatively low impedance compared to encasing formation are well detected and have been assigned to different classes, probably depending on their petrophysical parameters.

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hydrocarbon content (Figure 6). Similar anomalies were detected elsewhere in the dataset.

![Figure 5: Result of the SGNN seismic facies prediction on a penetrated unit. The method detects a massive sandy lobe intersected by erosive channels. The lobe is described by several seismic facies with a geologically consistent distribution. Up dip from the well penetration, a singular class (in red) should be highlighted.](image)

![Figure 6: Cross plot of the neuron of the strong anomalies detected up dip to the well. The amplitude versus angle plot at the top of the unit shows a strong intercept with a strong gradient.](image)

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Geobody detection has been applied on these anomalies to understand their spatial organization and their lateral extension. Figure 7 shows the geobody corresponding to the Arawa lobe (Figure 5) anomaly in depth. In this case, no conformity to the structure is observed and there is no evidence of a stratigraphic trap (continuous lobe deposits interpreted from seismic facies classification). Thickness computation of the sandy lobe unit cross plotted against amplitude shows that this amplitude anomaly is likely due to a tuning effect.

![Figure 7: Amplitude anomalies in depth against structural and stratigraphy. No evidence of closure.](image)

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CONCLUSIONS

The new classification technique applied on multi-dimensional data shows its advantages in the interpretation and reservoir evaluation process. The classification process does not only focus on the background trend but also provides reliable detailed information on the outliers which are important geological features for the E&P. Applied on pre-stack collections, the algorithm reduces information in a reliable manner. Indeed, in our example, sandy turbidites are better detailed than non-reservoir formation despite fewer occurrences. The algorithm discriminates AVA responses without requiring an explicit relationship between amplitude and offset. This discrimination should be an added value to the AVA study. The fact that the result is a seismic facies cube enables easy extraction of the different geobodies based on their class or a combination of different classes. This represents an economy of time compared with classical deterministic seismic picking.

This new seismic classification shows good discrimination between reservoir and background with less time and effort, and further validates the conventional AVAZ characterization, reducing the overall risk associated with new prospects.

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EDITED REFERENCES
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