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3D Seismic waveform classification

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Summary

Pattern recognition have been used for years in interpretation and reservoir characterization workflows, but with the advent of the technology it has transformed from purely visual inspection based to, automated unsupervised and supervised classification which can help in identification of subtle patterns hence allowing Geoscientist in identification of subsurface characteristics and exploiting the information in the seismic data.
Seismic waveform shape and character define facies with significant detail compared to time and amplitude mapping. A new 3D waveform seismic facies classification scheme has been presented in this paper. Unlike the traditional seismic facies classification methodology, classification using the 3D sub-cube is done using a K-means (MacQueen, 1967) or SOM Kohonen (1995) algorithm. The clustering is done in an n-dimensional attribute space. A cross distance matrix for all classes is computed to assess the amount of confidence for the classification results. The main advantage of using 3D sub-cube like objects for classification is ability to do classification for very thin layers with vertical size less then vertical seismic resolution. The use of computation sub-cubes stabilizes the calculation results. The main output is a distribution map of the classes and maps of probabilities (or similarity) for every class type. A class typical waveform and sub-cube for every class is automatically generated. The supervised mode allows probabilistic output that facilitates the interpretation of the end result.

Introduction

A fast 3D waveform classification scheme has been developed based on the SOM or K-Mean. The seismic amplitude or any attribute be can be taken as input for the classification procedure. Seismic waveforms or segments of traces are classified in order to define seismic facies changes in a specific interval which can be two geologic formations or constant interval.
Along with the facies distribution map of the classes, probabilities maps (or similarity) for every class type is also generated. Furthermore, a class typical waveform and typical sub-cube for every class is generated.

Method

Objects for the classification scheme are 3D waveforms or seismic sub-cubes. The latter allows a certain degree of averaging before the classification is done. Waveforms in sub-cubes (3D) have the following advantages:

- It allows to get classes with locally varying seismic signals – faults, turbidities etc.
- Geological objects with dipping seismic signal, like clinoforms, are better resolved.
- Input data smoothing and more stable results.

The procedure consists of a learning phase with class typical waveform computation and a classification step. The first step can be done in several ways:

- Automatic definition by applying a "K-means" algorithm (MacQueen, 1967) or SOM Kohonen (Kohonen, 1995), which allocates "clusters" with a compact distribution of similar waveforms.
- Semi-controlled classification with definition of point sets which correspond to the exact location of 3D waveform. Usually these are well locations where reservoir parameters are known. This is allow to find similar places in the layer via seismic 3D waveform similarity.
- Supervised approach with predefined waveforms taken from an external source, for instance from a synthetic modeling package where the reservoir parameters are known (Balz et al., 1999; Veeken 2007). The influence of many reservoir characteristics is modeled and various parameters can be changed at the same time to build a large suite of scenarios. The class specific master trace is described in a statistical way as several petrophysical models may give the same modeled seismic response. This supervised method is of great help for the interpretation of the classification output.

The second stage is the classification step. The similarity (or probability) is calculated as a measure for the degree of resemblance of the master set of traces (sub-cube) to every classified sub-cube. The highest probability range determines the class category for the sub-cube under examination (Figure 1).

During the classification, that uses the "K-means" algorithm or SOM Kohonen, two objects (waveform segment or set of waveform segments – sub-cube) will be in the same class if their waveforms have some kind of similarity. A measure for the amount of "similarity" can be calculated from the distance between the waveforms in a so-called n-dimensional cross plot. Mathematically every object can be represented by a point in a multi-dimensional space. In our seismic classification scheme every dimension corresponds to the sample position on the waveform. The distance can now be taken for example as the square difference between two waveforms (*L2* method). The mathematical distance in such a cross plot can be described as follows:

Let object O_i be a sub-cube where every trace have a set of measurements $X_i = \{x_i^1, x_i^2, ..., x_i^n\}$,
In our case every measurement is the sample value in the seismic trace. And object O_j is the second sub-cube which have the same size and measurements $X_j = \{x_j^1, x_j^2, ..., x_j^n\}$, it represents also sampled values in the seismic trace (Figure 1).

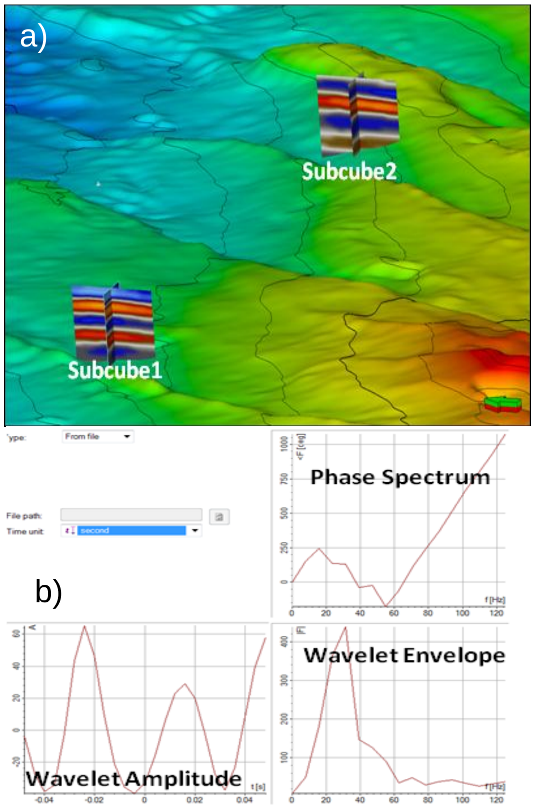

Figure 1: a) Two sub-cubes with two objects for calculating a measure of similarity-distance in the multi- dimensional domain b) Typical waveform at central trace in sub-cube1 for one of the classes computed by the waveform classification algorithm.

Self-Organizing Map (SOM) by Kohonen (1995) use scaling multi dimensional data (sub cube traces data) to two dimensional (in our case – one dimensional) map. Every neuron can be use like typical object for classification.

In this case distance (measure of similarity) between these two objects can be calculated in different ways:

$$M_{L1}(O_i,O_j) = L_1(X_i,X_{j)} = \sum_{trace}^{sub\text{-}cube} (\frac{1}{n}\sum_{k=1}^{n}\left|x_i^k - x_j^k\right|) \quad (1)$$

$$M_{L2}(O_i,O_j) = L_2(X_i,X_j) = \sum_{trace}^{sub\text{-}cube} (\frac{1}{n}\sqrt{\sum_{k=1}^{n}(x_i^k - x_j^k)^2}) \quad (2)$$

$$M_{COR}(O_i,O_j) = COR(X_i,X_j) \quad (3)$$

$$M_{FUR}(O_i,O_j) = L_2[F(X_i),F(X_j)] \quad (4)$$

$$M_{L2+COR}(O_i,O_j) = (L_2(X_i,X_j) + L_{COR}(X_i,X_j))/2 \quad (5)$$

where *L1* and *L2* are measure of similarity, M_{COR} is the "correlation coefficient". M_{FUR} is a measure of similarity amplitude spectrum difference and *F(Xi)* is Fourier transfer of function *Xi* and where (5) is a mixed measure of similarity that is normally used by default.

All distance measurements are normalized to range between 0 (non-similar) and 1 (similar). This normalized distance value is closely correlated to "probability" or degree of similarity. The similarity distance between objects in the n-dimensional space plot is determined by different calculation methods: Correlation + L2 (using coefficient of correlation (3) and L2 (2) method (Neff et al. 2001); L1 (1) (abs difference), L2 (2)(square difference), Average difference (average for every trace in sub-cube L2 between objects), Spectrum difference (4) (amplitude spectrum L2 difference).

The layer or investigation zone can be defined in two ways:

- An interval between top and bottom surfaces (see Figure 2).
- A constant thickness interval below the top surface.

Results of the classifications can be presented in surface (Figure 3 –a) or in cross sections (Figure 3 – b).

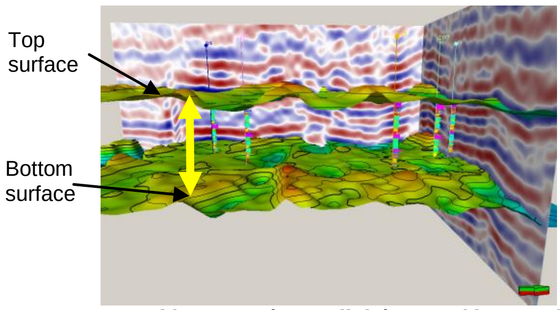

Figure 2: Top and bottom surfaces will define variable interval for waveform classification.

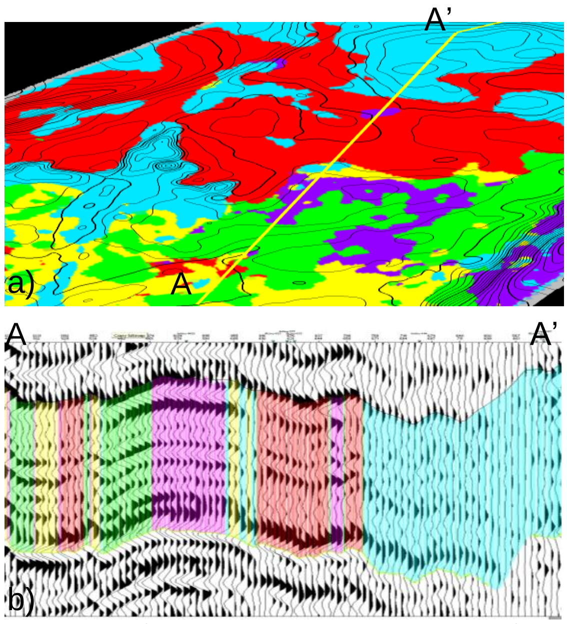

Figure 3: Classification results and possible visualization of it on surface - a) and on cross-section - b).

Examples

Seismic amplitude data is used as input with two horizons as the top and the base for unsupervised classification, number of class were input being the zone of interest and the other geologic understanding in the area, clearly showing the channel in red facies (Figure 4 & 5).

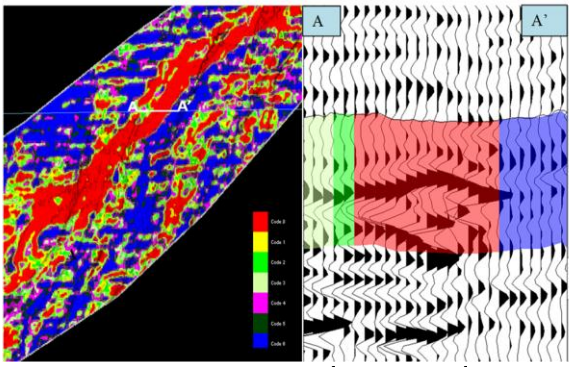

Figure 4: Being sensitive to waveform seismic facies map reveals deeper insights into the seismic response. (a) 3D map view of output classes and (b) seismic cross-section with classes in interval strips along section view A-A' showing the variation in the waveform

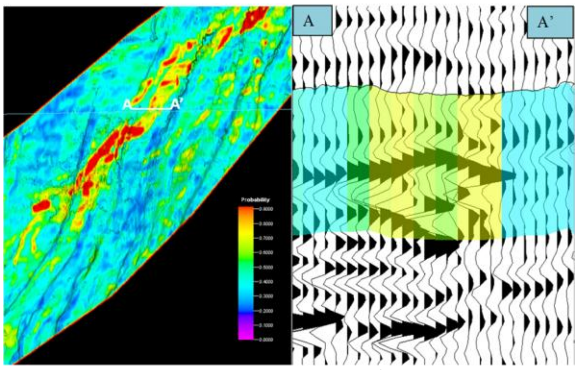

Figure 5: a) Probability (or similarity) of all traces with the master trace of the red class and (b) probability interval cross-section along seismic line A-A'.

Figure 6 show classification result for thin layer (~ 6 millisecond) via sub-cubes (6ms x 7 x 7 traces). In this case vertical wavelet is too small to do classification and lateral signal used to define seismic facies.

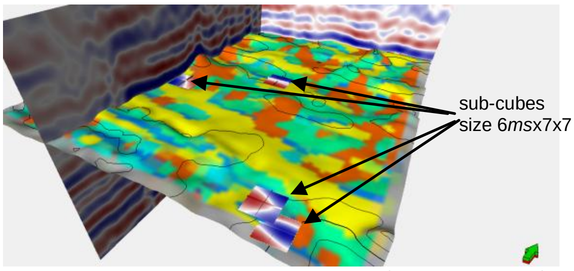

Figure 6: Thin layer (6 milliseconds) classification example for seismic facies detection for carbonate layer. Picture is shown 3d view of the horizon with classes and sub-cubes locations for the class typical 3D waveform (sub-cube 6ms x 7x 7 traces) for every class.

Figure 7 shown classification results for thin continental sedimentary layer. We use 6 milliseconds layer for cube with 2 milliseconds sample rate. For this case we used two approaches for classification. First approach is conventional classification based on single trace waveform. It is clear to see that in this case the results looks very similar to seismic amplitude slice. Also some small details what can be seen on seismic slice (Figure 7, a) is missing on the classification map (Figure 7, b). Second approach is based on 3D waveform classification. In this case the results (Figure 7, c) are much better and allow to detect Paleo Rivers or other objects with significant sand thickness like shown on Figure 8.

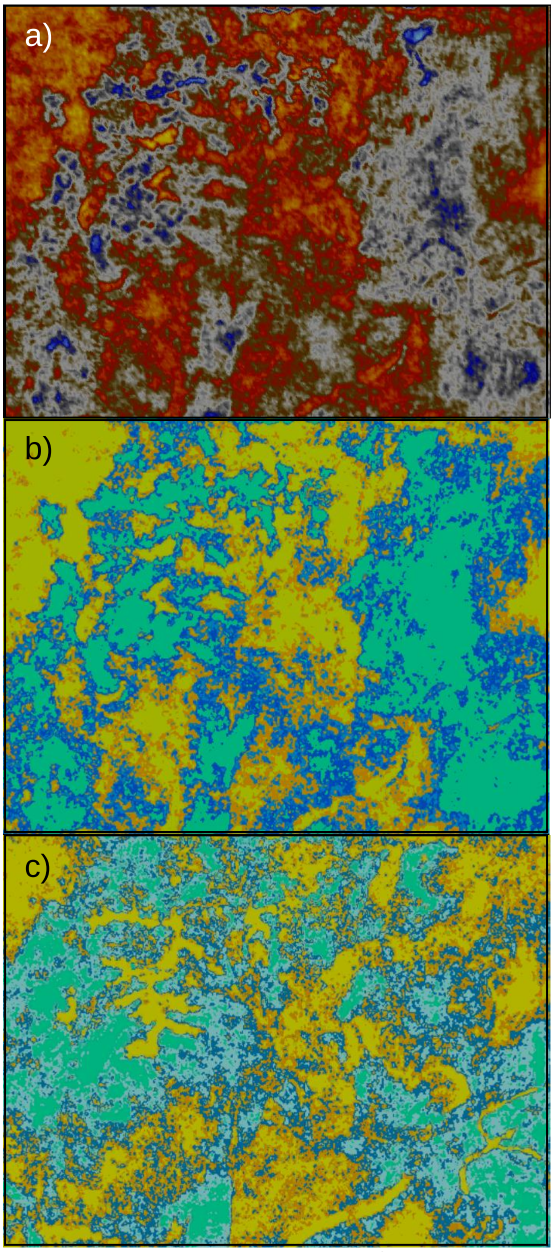

Figure 7: Thin layer (6 milliseconds) classification example. a) - Seismic amplitude slice via center of the layer. b) - classification result based on single trace waveform. c) - classification result based on 3D waveform (sub-cube 6ms x 3 x 3 traces).

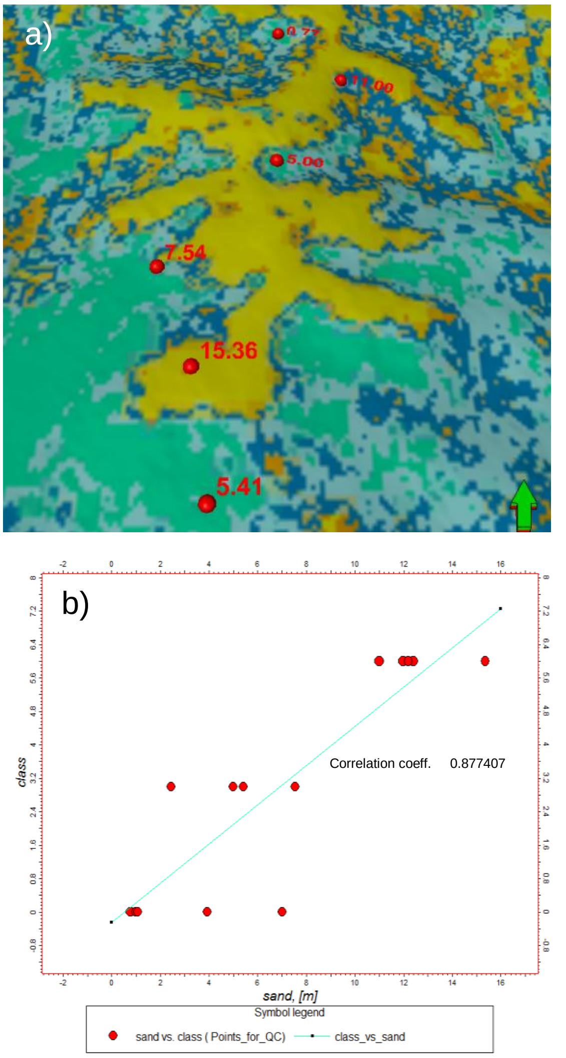

Figure 8: a) - fragment of classification result shown on Figure 6 with well position and sand thickness in meters. b) – correlation between sand thickness and classes.

Conclusion

The 3D waveform classification scheme, based on a K-means or SOM Kohonen methods, is a powerful tool to classify seismic data relatively fast and to delineate seismic facies units in a true 3D sense.
The main advantage of using 3D sub-cube like objects for classification is ability to do classification for very thin layers with vertical size less then vertical seismic resolution. In this case the technology can be used for lateral facies detection like faults, fracture zones or Paleo Rivers. The capabilities of a seismic reservoir characterization workstation are exploited to visualize the results in a convenient way and hence good connectivity with standard computation functionalities is ensured. An elementary processing rule applies: the cleaner the input data, the more reliable the output will be. The use of computation sub-cubes stabilizes the calculation results.

Usefulness of the classification scheme always needs to be verified on a case-by-case basis. Subtle differences in the input data can be rapidly highlighted by this method that would remain undetected by conventional data analysis. Also other attributes than seismic data cubes can be used as input.
The method is flexible, very fast, requires very limited user intervention and a robust workflow is proposed. The supervised option facilitates the interpretation of the classification results considerably and makes a probabilistic approach to the facies interpretation possible.

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