Z-99 Unsupervised Seismic Facies Classification Using Matching Pursuit and Self Organizing Maps

MARCÍLIO C. MATOS[1,3], PAULO L.M. OSÓRIO[1] AND PAULO R.S. JOHANN[2]

[1]*Pontifícia Universidade Católica, DEE, Rua Marquês de São Vicente, 225 , 22453-900 - Rio de Janeiro-BRAZIL*

[2] *Petrobras*

[3] *Military Institute of Engineering*

Abstract

A new alternative to build seismic facies maps is presented. We propose to use matching pursuit with time-frequency dictionaries in each geological oriented segment of the temporal seismic trace associated with the Self Organizing Maps (SOM) as a clustering tool. Jointly, they could be used as a seismic facies estimator. The technique was applied to a real data from a deep-water field in the Campos Basin, Brazil.

Introduction

Independent of the methodology adopted to perform the seismic facies analysis, the geological oriented spatial and temporal segmentation of the reservoir region should be carefully done. Depending on the complexity of the reservoir system, seismic data quality, and the experience of the interpreter, the level of confidence in an interpretation can vary from very high to very low [1]. Therefore, any interpretation error could lead to wrong or noisy results. Specially, when using seismic trace shapes, defined by the values of the seismic samples along each segmented trace, as the seismic input attributes to the chosen seismic facies algorithm. These facies analysis artifacts are introduced because seismic waveform in the reservoir delimited area changes quickly as a function of the interpretation, then waveforms with almost the same shape could be assigned to different classes due only to their different phases.

It is known that variations of the frequency content of a seismic trace with time carry information about the properties of the subsurface reflectivity sequence [2]. Consequently, seismic trace time-frequency analyses could provide an unconventional way to reservoir characterization. Some other woks [2], [3], had shown how to obtain some analogous classical attributes as the mean frequency and the phase through time frequency distributions. Specifically, in this work we propose to use the time-frequency properties of the atoms obtained after the matching pursuit signal representation [4], jointly with Self Organizing Maps [5] as an unsupervised seismic facies analyses system.

Seismic Facies Analysis by clustering of the SOM

Among the statistical and neural networks unsupervised seismic pattern recognition algorithms used by the industry, the SOM has become one of the most popular tools [6]. This fact is mainly due to the fact that the SOM algorithm preserves the similarity by grouping similar input data. Therefore, the estimation of the number of different seismic facies present in the data is still empirically determined. One powerful way to estimate it and to classify the seismic data, is to cluster the SOM constructed with a number of prototype vector much greater than the expected number of facies as showed in [7], [8].

Therefore, when the reservoir horizon interpretation is noisy as shown in Figure 2(a) the seismic facies classification, following the same methodology used in Figure 1, is not well done as shown in Figure 2(b).

Mallat's Matching Pursuit algorithm as a time-frequency event locator

Mallat [4] showed that any signal could be decomposed into a linear expansion of waveforms that are selected from a redundant dictionary of functions. Then, given a set of functions $D=\{g_1, g_2,\ldots,g_n\}$such that $||g_i||=1$, an optimal approximation can be obtained as an expansion of the M functions properly selected from the dictionary, which minimizes the approximation error given by the following equation:

$$e = \left\| f(t) - \sum_{i=1}^{M} w_i g_{g_i}(t) \right\|$$

where $\{g_{g_i}\}_{i=1,2,\cdots,M}$ represents the indexes of the chosen functions g_{g_i}.

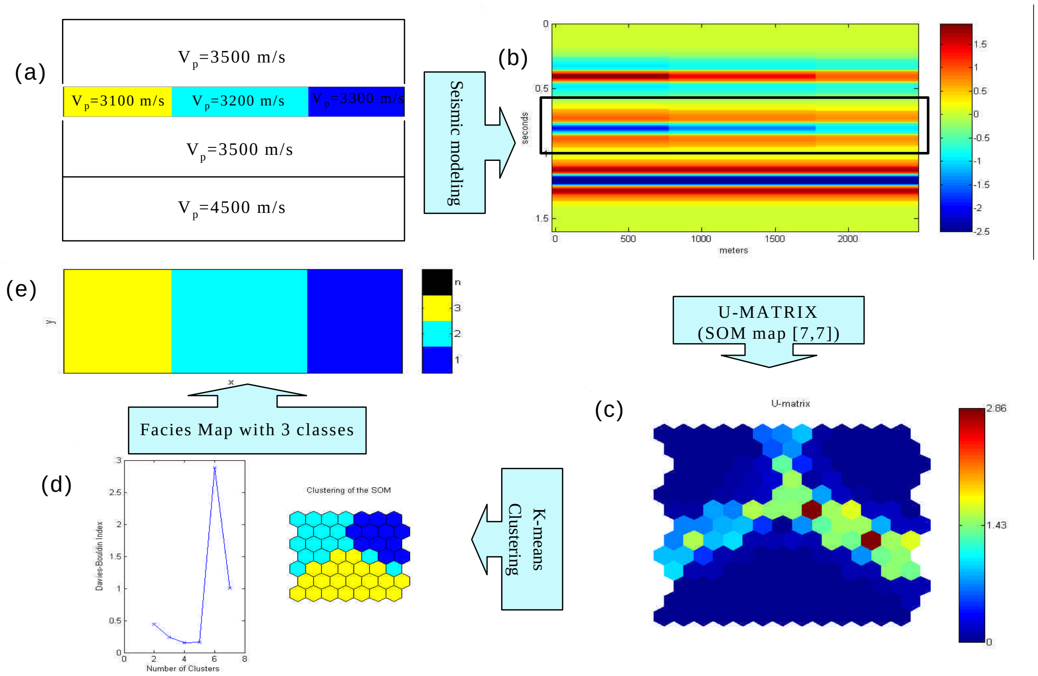

Figure 1: (a) Geological model; (b) Seismic model with 2 identical 2D lines; (c) U-matrix of the SOM; (d) Clustering of the SOM; (e) Facies map.

Basically, the matching pursuit algorithm searches step by step for a function g_{g_i} which best matches the signal *f(t)*. After the first iteration the best searching processes continues with the residual function obtained after subtracting the results of the previous iterations, as shown bellow:

$$\begin{cases} R^0 f = f \\ R^n f = \langle R^n f, g_{g_n} \rangle g_{g_n} + R^{n+1} f \\ g_{g_n} = \arg \max\limits_{g_{g_i} \in D} \left| \langle R^n f, g_{g_n} \rangle \right| \end{cases}$$

It could be proved that for a complete dictionary the procedure described above converge and thanks to the orthogonality between $R^{n+1}f$ and g_{g_n} in each iteration, the process implies energy conservation:

$$\| f \|^2 = \sum_{n=0}^{m-1} \left| \langle R^n f, g_{g_n} \rangle \right|^2 + \| R^m f \|^2$$

The time-frequency distribution of the signal is described as a function of the Wigner distribution of each selected function of the dictionary, which are called atoms, and is free of cross terms:

$$\mathrm{E}f(t,w) = \sum_{n=0}^{M} \left| \langle R^n f, g_{g_n} \rangle \right|^2 W g_{g_n}(t,w)$$

Among some of the function dictionaries available [9] the Gabor dictionary provides optimal time-frequency localization [4] and it is constructed by dilating, represented by the *s* parameter, translating, represented by the *u* parameter and modulating, represented by the *x* parameter, a single Gaussian window function *g(t)*of unit norm:

$$g_g(t) = \frac{1}{\sqrt{s}} e^{-p\left(\frac{t-u}{s}\right)^2} e^{jxt}$$

Matching Pursuit with Gabor dictionary and the SOM

Figure 3 shows the reconstruction with only four atoms of the three different facies seismic traces generated using the model shown in Figure 1. The reconstructed seismic traces show very consistent waveforms maintaining the main seismic event characteristics. Consequently, the original signal could be represented with a desired error by the main M atoms, selected from the Gabor dictionary using the matching pursuit algorithm. The main M atoms could be represented by their formation parameters: u, s, x, plus their individual energy contribution. Therefore, jointly, through the SOM clustering these parameters could indicate similarities between the seismic events. The proposed methodology is:

1- Segment each seismic trace around a geological oriented region;
2- Decompose each segmented trace into M atoms using the matching pursuit algorithm with the Gabor dictionary and create an attribute vector for each seismic trace consisting of the energy plus the scale and the frequency parameter of each atom decomposed;
3- Visualize the (SOM) formed using the input space seismic attributes, as described in the last step;
4- Cluster the SOM using K-means, or other clustering algorithms, with as many clusters as shown on the SOM map or use some empirical metrics as the Davies-Bouldin index [7].
5- Construct and interpret the facies map.

Figure 2(c) shows the methodology applied to the synthetic data, which was segmented using a noisy horizon interpretation. The result seems very good and shows that the method is less time invariant sensitive.
The same methodology was applied to a real data from a deep-water field in the Campos Basin, Brazil. In this case, 16 seismic samples, or equivalently a 48 ms window was segmented around the base of the reservoir. Despite using a longer time window than the known stratigraphic unit, the resulting seismic facies map, showed in Figure 4, seems very consistent with earlier supervised analyses [10].
The whole algorithm, from SEGY files and horizon reading to seismic maps visualization, was implemented using Matlab from Mathworks and the SOM toolbox from Helsinki University of Technology.

Conclusions

Results have shown that the new method proposed for seismic facies analysis can be an alternative way to 3D or 4D seismic reservoir characterization and it seems that changes in the size of the analyzing window could have little influence in the facies analysis process. Particularly, we propose a new approach to extract reliable seismic attribute as input data for self-organizing map visualization and clustering of an entire volume of seismic data of a deep-water field in the Campos Basin, offshore Brazil.

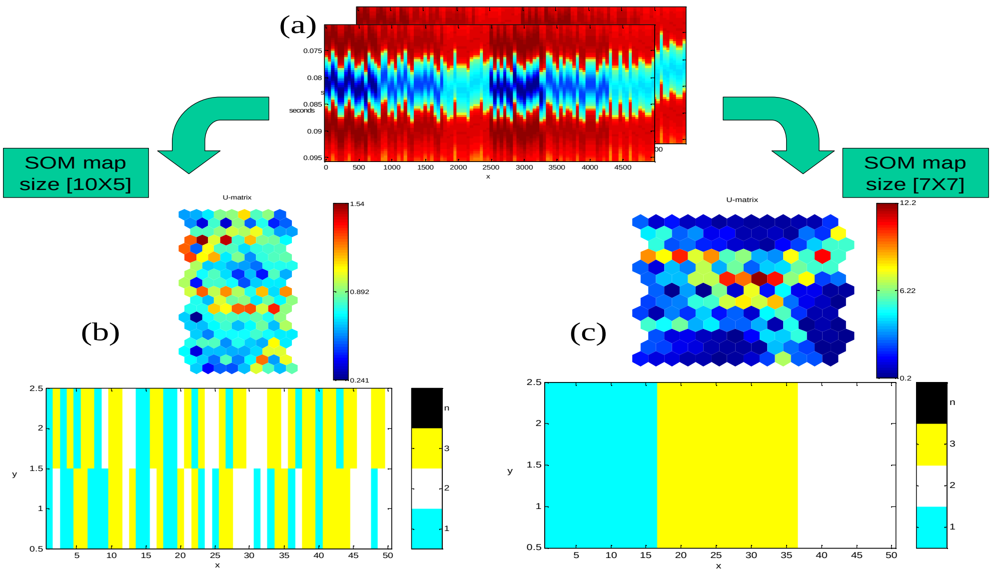

Figure 2: (a) Seismic interval obtained using noisy horizon interpretation; (b) Seismic facies analysis using the waveforms as input attributes; (c) Seismic facies analysis using attributes generated by the matching pursuit algorithm.

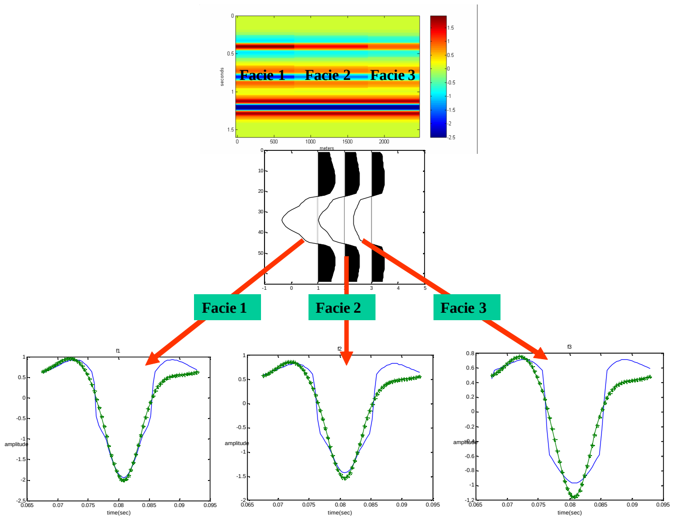

Figure 3: Waveforms reconstruction using the 4 most important Gabor atoms

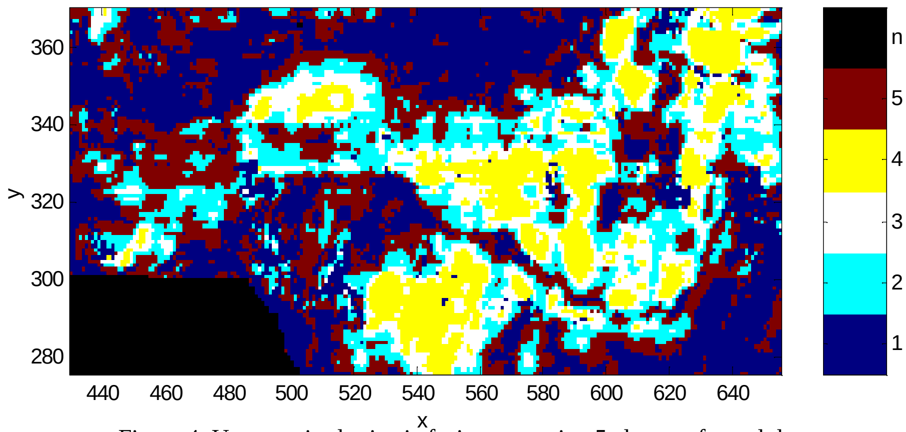

Figure 4: Unsupervised seismic facies map using 5 classes of a real data.

Acknowledgments

The authors would like to thank ANP (Brazilian Petroleum Agency) and Petrobras for the permission to use the seismic data contained herein and to Petrobras financial support though the PRAVAP 19 research program. We also would like to thank Evaldo C. Mundim, Djalma M. S. Filho and Marcos S. Santos from Petrobras and Marco Cetale Santos and Felipe P. Loureiro from PUC-Rio for their comments and help.

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