Using Matching Pursuit and Self Organizing Maps for Seismic Reservoir Characterization of a Deep-water Field, Campos Basin, Offshore Brazil

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Summary

We propose to use the matching pursuit with time-frequency dictionaries algorithm applied in each geological oriented segment of the temporal seismic trace jointly with the clustering of the Self Organizing Maps (SOM) as a new alternative to build seismic facies maps. The technique was applied to a real data from a deep-water field in the Campos Basin, Brazil.

Introduction

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 (Rankey and Mitchell, 2003). Specifically, when performing seismic facies analysis for reservoir characterization, any interpretation error could lead to wrong or noisy results.

The variations of the frequency content of a seismic trace with time carry information about the properties of the subsurface reflectivity sequence (Steeghs and Drijkoningen, 2001) and even some analogous classical attributes as the mean frequency and the phase through time frequency distributions could be generated through seismic trace time-frequency analyses (Steeghs and Drijkoningen, 2001), (Verhelst, 1998). But, the derivation of some attributes directly from the time-frequency representation could not be enough to represent and characterize the time-frequency behavior of the seismic facies in the area of interest. This work proposes to use the whole time-frequency properties of the atoms obtained after the matching pursuit signal representation (Mallat and Zhong, 1993), jointly with Self Organizing Maps (Kohonen, 2001) as an unsupervised seismic facies analysis system.

Mallat's Matching Pursuit with Gabor dictionary algorithm

Matching Pursuit is a very flexible way to analyze signals in time and frequency jointly. Mallat (Mallat and Zhong, 1993) showed that any signal could be decomposed into a linear expansion of waveforms that are selected from a redundant dictionary of functions. Given a set of functions $D=\{g_1, g_2,\ldots,g_n\}$ such that $||g_i||=1$, an optimal approximation of a function $f(t)$ can be obtained as an expansion of the M functions properly selected from the dictionary:

$$f(t)=\sum_{i=1}^{M} a_i g_{\gamma_i}$$

which minimizes the approximation error given by:

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

where $\left\{ g_{\gamma_i} \right\}_{i=1\cdots M}$ represents the indexes of the chosen functions g_{γ_i} .

Basically, the matching pursuit algorithm searches step by step for a function g_{γ_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:

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

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_{γ_i} in each iteration, the process implies energy conservation:

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

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:

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

Among some of the function dictionaries available (Jaffard et al. 2001) the Gabor dictionary provides optimal time-frequency localization (Mallat and Zhong, 1993) and it is constructed by dilating, represented by the s parameter, translating, represented by the u parameter and modulating, represented by the ξ parameter, a single Gaussian window function $g(t)$of unit norm:

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$$g_\gamma(t) = \frac{1}{\sqrt{s}} e^{-\pi\left(\frac{t-u}{s}\right)^2} e^{j\xi t}$$

As the number M of the atoms increases the better is the function approximation. But, Figure 1 shows the reconstruction with only four atoms of the three different facies seismic traces generated using the model shown in Figure 2a, and the reconstructed seismic traces show very consistent waveforms maintaining the main seismic event characteristics. Consequently, the original signal could be well represented with a desired error by the main M atoms, selected from the Gabor dictionary using the matching pursuit algorithm.

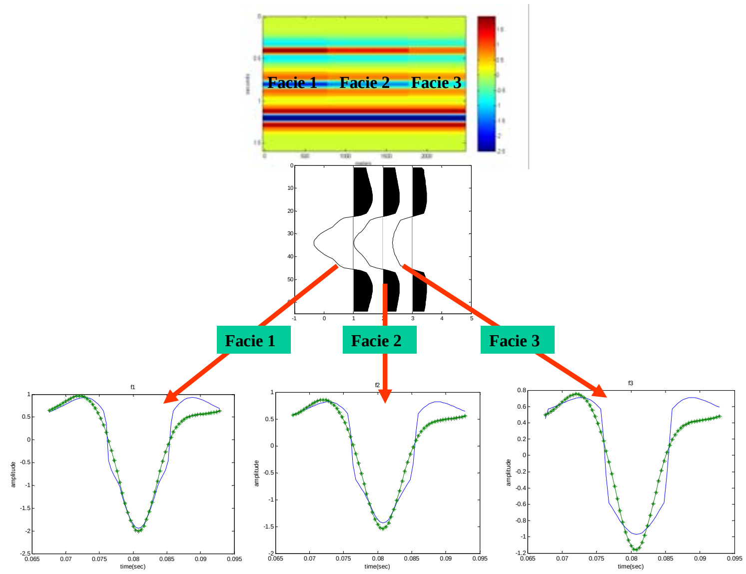

Figure 1: Waveforms reconstruction using the 4 most important Gabor atoms

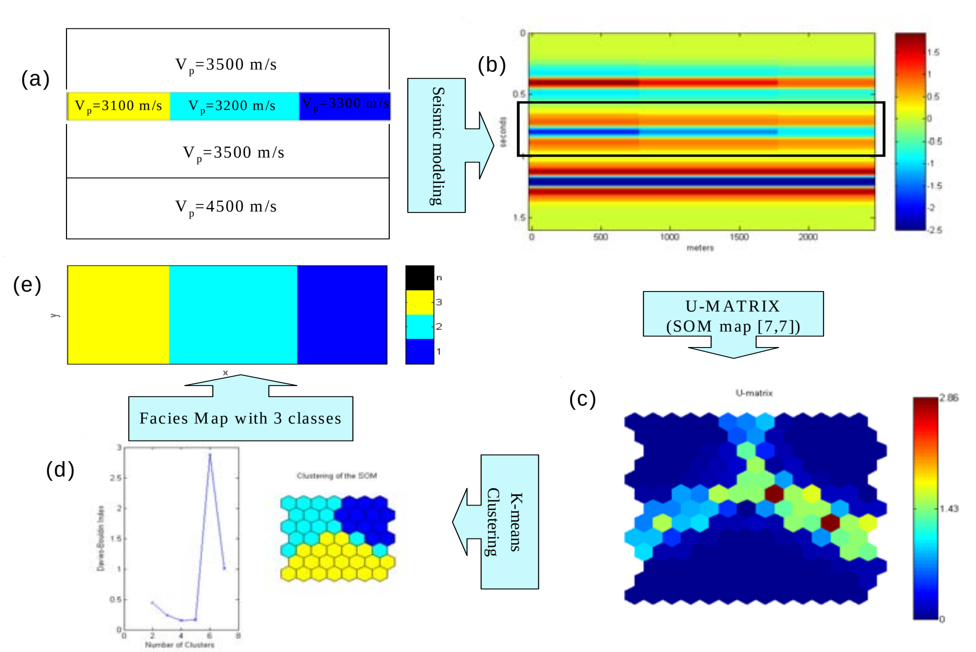

Figure 2: (a) Geological model; (b) Seismic model with 2 identical 2D lines; (c) U-matrix of the SOM; (d) Clustering of the SOM; (e) Facies map.

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Matching Pursuit and the seismic facies analysis by clustering of the SOM

One powerful way to estimate the number of seismic facies and to classify the seismic data, through non-supervised muti-attribute analysis, is by clustering of the Self Organizing Maps (Matos et al., 2003), (Matos et al., 2003). Figure 2 synthesizes the process, when the seismic attributes are the waveform shapes (the seismic instantaneous amplitudes) for a synthetic data with three different facies, and the results are very good. But, when the attributes are extracted using a noisy seismic interpretation the results are poor as shown in Figure 3b.

Therefore, after the decomposition of a signal using the matching pursuit algorithm, the main *M* atoms obtained could represent the signal by their formation parameters: *u*, *s*,ξ, plus their individual amplitude $\left\langle R^n f, g_{\gamma_n} \right\rangle$ contribution or their equivalent energy contribution, and those parameters could be used as seismic attributes input to a seismic facies analysis system.

But, the parameter *u*, which represents the atom time location, is still sensitive to noisy interpretation. Then, despite the use of the parameter *u* directly, it is preferable to use the time shifts from the first atom as one of the attributes.

Then, the parameters obtained through matching pursuit could indicate similarities between the seismic events when used jointly with the clustering of the SOM seismic facies analysis algorithm. 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 amplitude contribution or the energy, plus the scale, plus the frequency parameter of each atom decomposed; and the time shift from the first atom of the atoms 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 (Matos et al., 2003).
5- Construct and interpret the facies map.

Figure 3(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 the use of 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 (Johann, 1997).

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.

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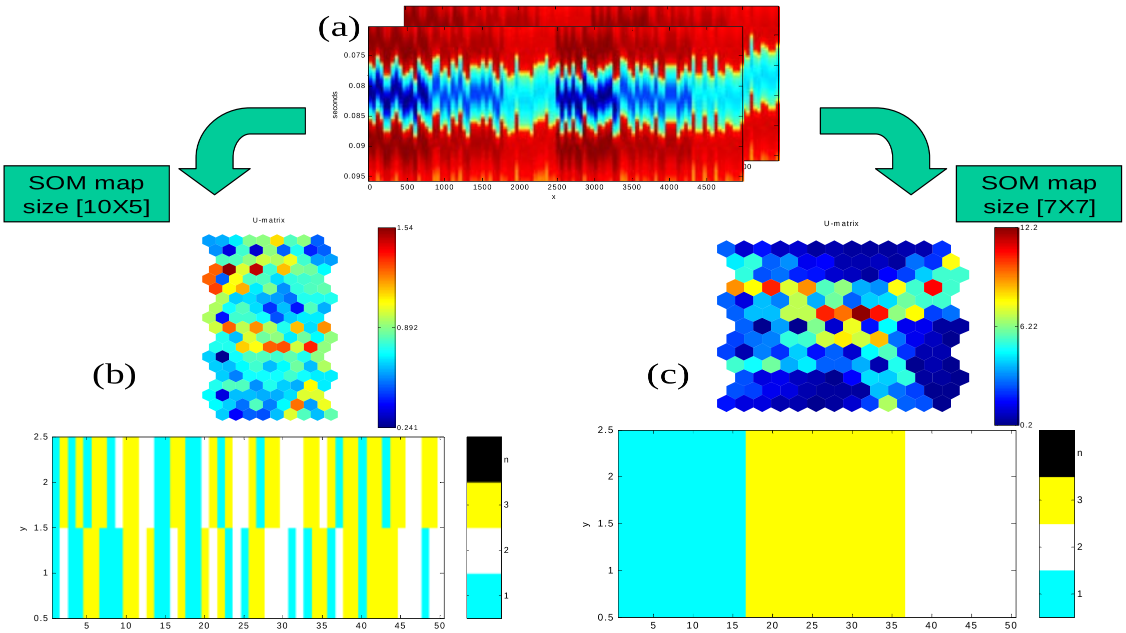

Figure 3: (a) Seismic interval obtained using noisy horizon interpretation; (b) Seismic facies analysis using the waveforms as input attributes; (c) Seismic facies analysis using attributes generated by the matching pursuit algorithm.

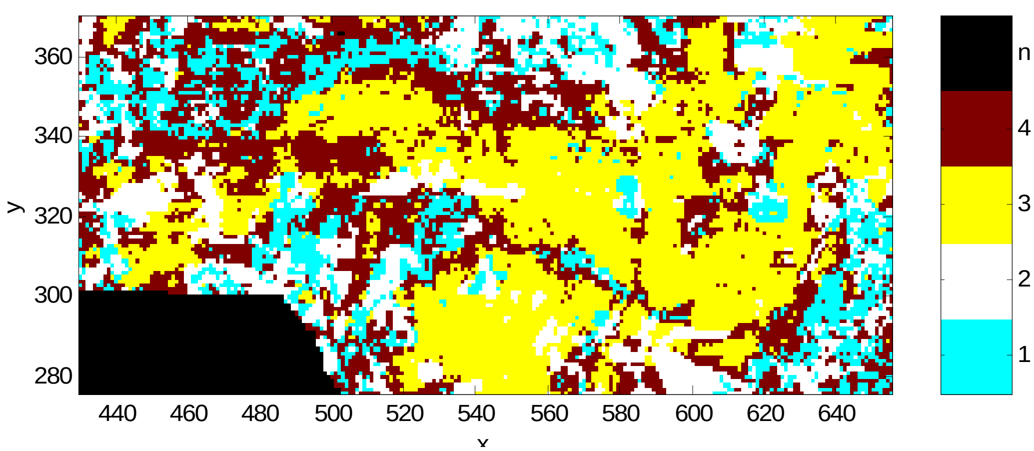

Figure 4: Seismc facies analysis of a real data using the methodology proposed