

Seismic Pattern Recognition Using Wavelet Transform and Seismic Attributes

Margarita Fernández¹, Adriana Mavilio¹, Juan Ramón Jimenez³, Nieves Henriquez³

¹ Technical University of Havana, ISPJAE
Ciudad Habana (Cuba)

mflimia@electrica.ispjae.edu.cu,
adriana@electrica.ispjae.edu.cu

² PDVSA, INTEVEP, Caracas (Venezuela)

Jrjim@intevp.pdv.com, henriqueznp@pdvsa.com

Abstract

Seismic pattern recognition was carried out based on a comparison of seismic reflection traces of an interest region with those taken of a geologically well understood zone. The pattern was constructed from seismic traces corresponding to this reference zone. A segmentation task was performed, shifting a window through the 3D seismic data of the whole study region following seismic horizons.

We obtained similarity maps considering texture feature and seismic attributes respectively. On one hand texture features were computed based on wavelet decomposition coefficients of the seismic trace segments inside the window. In this case, the Mahalanobis distance to the pattern was used to determine the gray tonalities of the similarity map. On the other hand, a set of seismic attributes was extracted from seismic traces and compared with the pattern ones. From this comparison a parameter, seismic similarity to the pattern, was obtained.

A similarity map was also generated according to the values of this parameter. A satisfactory agreement between both similarity maps was obtained

Key words: seismic pattern, texture, wavelet.

1. Introduction.

The determination of areas of seismic similarity to those of good petrophysical properties can be a powerful tool to support exploratory work by highlighting areas with higher priority of prospecting. This can be done generating similarity maps based on the recognition of seismic reflection patterns [1, 2, 3], which are extracted around two good producing wells belonging to the region.

In this work, we generate similarity maps by using two different methods: wavelet approach [4] and seismic attribute technique [5].

Wavelet transform is one of the main techniques for analysis of signals and images. This description provides information about the signal contained in ever-

smaller regions of the frequency domain, and thus provides a very powerful tool for the discrimination of similar textures. In the last decade much research work on texture analysis has been done using this technique [6, 7].

In another paper we report the results of the use of these techniques and Gabor filters for texture segmentation of a 3D seismic section [4].

Correlating various attributes with reservoir properties generally performs seismic attribute analysis. This correlation cannot be extrapolated from one reservoir to another. This task becomes more difficult as the number of attributes involved becomes larger. We use a similarity analysis [5] to summarize seismic attribute information into just one parameter. This method eases the analysis task.

2. Seismic Data

The size of seismic data volume is $(567 \times 166 \times 325)$ pixel³. The z-axis corresponds to time (one division equivalent to 4 ms). The seismic reflection signals with 325 samples are seismic trace segments recorded with a bin size of 30×30 m.

The x, y position of a good producing well was known. A window of $(10 \times 10 \times 9)$ pixel³ around the well (calibration point), corresponding to 100 seismic trace segments, was taken as reference area. The seismic trace segments inside this window, characterizing the internal stratification of this area, were considered to construct the pattern. The time length of this window plays an important role, since the good focus of the structural characteristics inside the seismic data volume depends on it. The time length of 9 elements (32 ms) was chosen taking into account the results of a correlation analysis [8], since for this time length the stratigraphic faults inside the seismic data volume were delineated more precisely.

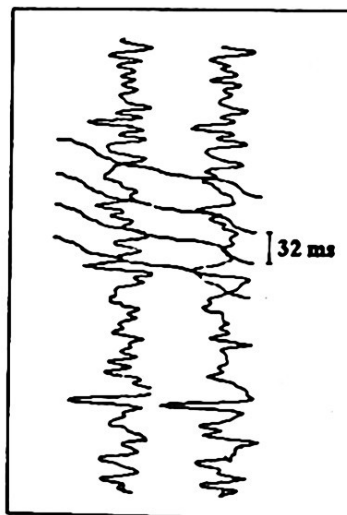


Figure 1. Trace segments extracted from the seismic data volume. The orientation of the sketched line segments follows the seismic horizon. They delimit the segmentation zones.

It was supposed that non-significant changes of the stratification take place inside the window.

The segmentation was carried out following a seismic horizon, at three different levels, as can be seen in Fig. 1.

The seismic data were supplied by the Venezuelan Enterprises PDVSA.

Texture Features.

The Wavelet Transform uses a family of wavelet functions and its associated scaling functions to develop the original signal in different frequency sub-bands. The decomposition procedure is successively applied to the lowest frequency sub-band to obtain the next level of resolution. The wavelet filters $\{g\}$ (bandpass) and scaling $\{h\}$ (lowpass) are followed by a two to one sub-sampling in the signal.

The results are a detailed signal containing high frequencies and one approximate that corresponds to the lowest frequency sub-band. The procedure is repeated on the approximated signal to obtain the next resolution level. Thus, the wavelet transform is performed through a pyramidal algorithm [6].

The Daubechies wavelet bases are orthonormal, of compact support and have been broadly used in signal and image processing.

In this work, Daubechies-2 orthogonal basis was applied until a decomposition level $J = 2$, taking into account the results of a numerical experiment performed in a prior work with other seismic data [4].

The next steps were followed for pattern construction:

- Each trace segment (with 32 time elements, after a cubic spline interpolation) from the reference area is decomposed by means of the 1D wavelet transform, obtaining finally 3 sub-signals (frequency channels), one approximate and two detailed signals.
- The pattern feature vectors are determined. The three components of these vectors correspond to the three frequency channels. These components are calculated according to (1-4). A gaussian-weighted average of them is performed on the reference zone. Also, the feature covariance matrices C_{cov} are calculated.

The features: energy (E), modulus (md), standard deviation (sd) and average residual (rms) were calculated for each frequency channel through the following expressions:

$$E = 1/M \sum_{j=1}^M |c_j|^2 \quad (1)$$

$$md = 1/M \sum_{j=1}^M |c_j| \quad (2)$$

$$sd = \sqrt{\sum_{j=1}^M \frac{(c_j - vm)^2}{(M-1)}} \quad (3)$$

$$rms = 1/M \sum_{j=1}^M |c_j - vm| \quad (4)$$

where c_j are the decomposition coefficients on a frequency channel, M is the number of coefficients corresponding to this channel, and \bar{vm} is the mean value of the channel coefficients.

4. Seismic attributes

Seismic attributes, defined as "any or all the extracted observations of the seismic data, that can help direct or indirectly to the exploration of hydrocarbons" [9] have been used for the prediction, estimate or extrapolation of the stratigraphic characteristics of the location. In this work we used them in order to evaluate similarity to a pattern.

The mean values (gaussian-weighted average) and the standard deviations of each attribute were calculated in the reference zone. The following set of independent seismic attributes was used: top amplitude, composite envelope amplitude, average instantaneous frequency, amplitude wt.average, instantaneous frequency, average vibration energy, instantaneous real amplitude and instantaneous quadrature amplitude. They were computed by using appropriate software (IC2 de Scott & Pickford).

The pattern attribute vector was conformed. The components of this vector are the mean values of these attributes.

5. Segmentation

In order to discriminate zones of different similarity to the pattern inside the seismic data volume, we generate the similarity maps.

A segmentation window with size $(10 \times 10 \times 9)$ pixel³ is shifted pixel to pixel following the seismic horizon for three different levels (see figure 1). The size of the window is a compromise between reliability of the estimates of the seismic textures and seismic attributes, and a wish of high resolution on the entire section.

In order to obtain the feature or the attribute vector of the window sample for each window location, we followed the same steps as in the case of the pattern construction. The sample vector was assigned to the window's central point.

The Mahalanobis distance:

$$D = \sum_{j=1}^4 (\mathbf{d}_j - \mathbf{d}_{pj})^T \left(\frac{\text{Cov}_{pj} + \text{Cov}_j}{2} \right)^{-1} (\mathbf{d}_j - \mathbf{d}_{pj}) \quad (5)$$

between the reference feature vector and the sample feature vector were calculated for wavelet approach. The degree of similarity between the sample inside the window and the reference texture can be expressed in terms of the inverse of this distance. In the expression (5) \mathbf{d}_j and \mathbf{d}_{pj} are the 3-dimensional feature vectors of the window sample and the pattern respectively. Here the index j specifies the type of feature. Cov_{pj} and Cov_j are the covariance matrices of the j -type feature for the pattern and the sample respectively.

For attribute analysis, the similarity parameter was calculated in two steps: classification and sum. In the first step, to each component of the sample attribute vector is assigned one or zero, depending on whether its value falls within an interval centered in the corresponding component of the pattern attribute vector plus-minus the standard deviation of this component. The second step is simply to add up all the binary components. The result is the value of the similarity parameter for that window location.

Obviously, the similarity parameter ranges from zero to the number of attributes employed in the process. The areas with a greater quantity of attributes similar to those of the reference point possess the highest values of this parameter.

6. Results.

Fig. 2 shows one of the similarity maps obtained through wavelet approach and attribute analysis for one of the three studied levels and for one of the two reference zones. In the first case is showed the Mahalanobis distance and in the second the similarity parameter. Lightest gray tones correspond to more similarity to reference zone and darkest tones correspond to zones, which are very different from it.

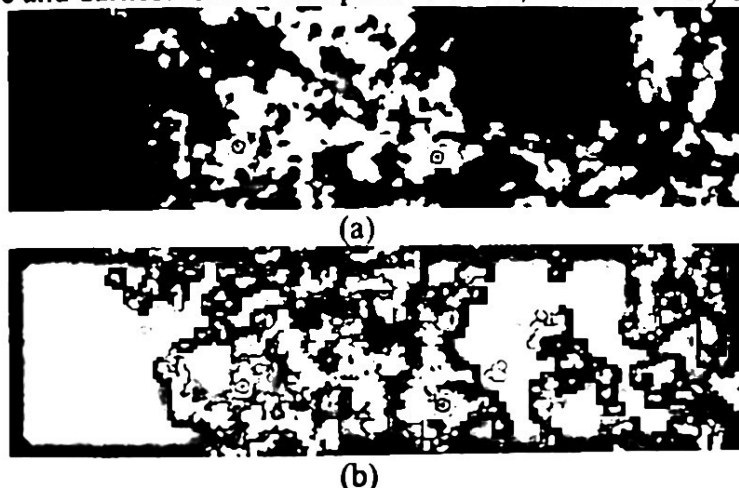


Figure 2. Similarity maps of a reservoir at a given level for reference well (producer). (a) Applying Wavelet Transform, Daubechies-2 orthogonal basis. (b) Applying seismic attribute similarity analysis.

It is important to point out the good qualitative agreement between the two similarity maps generated by both approaches in spite that is impossible to quantify the similarity between both methods because they are based in different features and used different discrimination

functions. This agreement is present also in the three studied levels and for the two reference zones.

The black zone at the left on the images has not any meaning, since it corresponds to a lack of seismic information.

Black points centered in black circles on Fig.2 indicate the locations of two good producing wells of similar known rock properties.

The reference zone is located around the control point represented in the similarity maps by the black point on a lightest gray zone, near the center of the images demonstrating its great similarity with the pattern. It is expected since we know that both wells have similar rock properties.

7. Summary and Conclusions.

We have used two approaches, attribute technique and wavelet transform to perform pattern identification in a 3D seismic section, following a seismic horizon.

A satisfactory agreement was obtained among both methods and it was shown that both provide effective tools for seismic pattern recognition.

As a result of these segmentations the location of a stratigraphic fault was found. Experts in this matter have corroborated this result. Both methods performed the right identification of zones around the good production wells.

The used features and attributes showed high discrimination power for different seismic textures.

The generated similarity maps can be used to identify zones with similar seismic response to the reference zone, in this case a good producing well. A comparative analysis of these two maps provides a guide to highlight prospective areas with higher priority.

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