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Wavelet transform analysis for lithological characteristics identification in siliciclastic oil fields

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ABSTRACT

In this work, we propose the application of the wavelet transform analysis in well-logs (radioactivity, resistivity and sonic) to identify facies. The wavelet transform is applied to a set of well-log data for identifying correlations between wavelet coefficients and lithofacies sequences. Our results indicate that the scales, in a multiscale analysis, are related to the rock thickness and depending on the scale used it is possible to identify other particular or general sequences. The results obtained are compared and corroborated by standard geological procedures for lithological characterization, indicating that the wavelet analysis provides qualitative guides for the identification of lithological properties in wells. All our analyses are based on a siliciclastic oil field that belongs to Chicontepec Formation of the Tampico–Misantla basin in Mexico.

1. Introduction

The primary objective in the hydrocarbon reservoir characterization is the identification of lithofacies, since they can be used to determine important characteristics of a geologic unit, such as mineral composition, sedimentary structures, geometry, depositional fabric, fossil content, and also can be used to infer origin (Crain, 1986; Rider, 1996). Traditionally, a lithological characterization is performed by direct measurements of cores, obtaining detailed information of the wells. However, the recovery of cores is expensive, its analysis is time consuming and its adequate interpretation depends on the experience of a geologist (Chang et al., 2000). This fact motivates the development of efficient and low-cost methodologies for the lithological description of wells. An important alternative is well-log analysis, because well-logs are records of the geological properties of subsurface rock formations at different depths that are usually recovered in most wells. Although well-log analysis is a useful tool for the lithological description of wells, the inherent complexity of the signals (e.g., pressure, saturation and types of fluids, size and form of pores) makes well-log interpretation not simple. Traditional techniques for well-log analysis (e.g., visual inspection) are not systematic and depend on the experience of the interpreter, and therefore can generate multiple interpretations (Lee et al., 2002; Tang and White, 2008). To discriminate the impact of these subjective differences, many computational algorithms have been recently proposed for automatic lithofacies identification. The most important of these are multivariable statistic and artificial intelligence methods (Chang et al., 2000; Chikhi et al., 2005; Delfiner et al., 1987; Enikanselu and Ojo, 2012; Tang and White, 2008). Although these methods show an important progress in automatic lithofacies prediction, they are not systematic (i.e., require parameter tweaking that depends on the interpreter's experience) and require a large amount of data, which is not always available.

Signal processing techniques also have been proposed for geophysics series analysis, such as Fourier analysis (Weedon, 2003), Wash transform (Lanning and Jonson, 1983; Maiti and Tiwari, 2005), fractal and multifractal analyses (Dashtian and Jafari, 2011; Hernandez-Martinez et al., 2013; Khue et al., 2002). Particularly, the wavelet transform has been widely used in geophysics analysis of data-series (Bolton et al., 1995; Guyodo et al., 2000; Jiang et al., 1997; Prokoph and Veizer, 1999; Torrence and Webster, 1999). For instance, Panda et al. (2000) used the wavelet transform for permeability data analysis, finding that the multiscale analysis provides guides for the determination of layer boundaries, faults, and fractures. Prokoph and Agterberg (2000) applied wavelet analysis to gamma ray logs to establish a correlation between different Milankovitch cycles, concluding that climatic cycles are an important factor in deposition. Alvarez et al. (2003) proposed the lithologic characterization of wells by the interpretation of wavelet coefficients and the energy of the wavelet transform. They used gamma ray logs and seismic traces of different wells, finding that the wavelet energy distribution corresponding to wells in sandstones is significantly different to those of the wells on gravel. Other authors have used wavelet analysis to determine fractal parameters in different well-logs, finding that a lower fractal dimension can be associated with sands and a greater fractal dimension to shales (Briqueu et al., 2010; Lopez and Aldana, 2007). The wavelet transform combined with other data-series analysis techniques has also been used. For instance, Pan et al. (2008) analyzed

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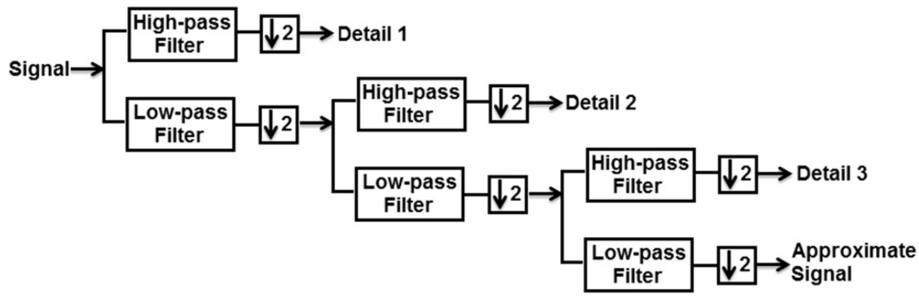

Fig. 1. Block diagram for decomposition into three levels of a signal.

spontaneous potential and gamma ray log data by the combination of the wavelet transform and Fourier analysis. They found that the wavelet coefficients reconstructed by Fourier analysis of gamma ray and spontaneous potential signals allow to identify formation boundaries. However, an important disadvantage is that the identification of the boundaries depends on the intensity fluctuations of well-log signals. Arabjamaloei et al. (2011) used a wavelet transform filter to identify changes in trends of the well-log signals that were related to lithology changes. To determine the most important changes an artificial neural network was incorporated, allowing the identification of the formation boundaries. Recently, Chandrasekhar and Eswara-Rao (2012) applied wavelet analysis to determine space-localization of the oil and/or gas formation zones. They analyzed different wavelets finding that the Gaussian function provides the best results for the identification of formation boundaries.

Therefore, several studies have demonstrated that the wavelet transform analysis exhibits qualitative clues for reservoir characterization. In this work, we present the application of wavelet transform technique to well-logs for lithologic characterization of a siliciclastic oil field. We have applied different wavelet-types to radioactivity, resistivity and sonic logs of wells belonging to the Chicontepec formation, Mexico. First, an exploratory analysis using different wavelet-types was carried out, identifying the wavelet-type most adequate for the well-log analysis. The wavelet scalogram and wavelet decomposition at different levels were applied to well-log signals in order to identify lithological properties. Our results indicate that the wavelet analysis provides reliable information about of lithological properties of the well, independently of the log that was analyzed. All results were compared and calibrated by standard geological procedures using well-log and core information.

2. Methodology

2.1. Wavelet transform

The usage of wavelet transform multiscale analysis applied to data-series has an important tradition in earth sciences (Bolton et al., 1995; Capilla, 2006; Guyodo et al., 2000; Jiang et al., 1997; Li et al., 2013; Prokoph and Veizer, 1999; Torrence and Webster, 1999). The principal aim of wavelet analysis is to determine the content of frequencies, in both scale and time, of the nonstationary signal. Such transformations are possible by using different shapes and sizes of functions called wavelets. A wavelet function is represented by

$$\psi_{u,s}(x) = \frac{1}{\sqrt{(s)}}\psi\left(\frac{x-u}{s}\right), \quad u>0, \quad s\in\mathbb{R} \tag{1}$$

where the function ψ is called the mother wavelet, s is the scale factor, that determines the wavelength, and u represents the shift of the wavelet (Goupillaud et al., 1985). In the wavelet transform, the signal analyzed is convolved with the mother wavelet and the transformation is computed for different segments of the data by means of the variation of s and u. A wavelet transform where shifts and dilations are continuously varied is called a continuous wavelet transform (CWT) (Goupillaud et al., 1985). CWT is a convolution of the signal $f(x)$ with a set of functions generated by the mother wavelet ψ and it is given by

$$CWT_f(u,s) = \int_{-\infty}^{\infty} f(x)\psi_{u,s}(x)dx = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{\infty} f(x)\psi\left(\frac{x-u}{s}\right)dx. \tag{2}$$

On the other hand, the transformation where the variations are represented by powers of an integer n (usually in dyadic increase) is called a discrete wavelet transform (DWT) (Daubechies, 1988). In the discrete domain, the scale and shift parameters are discretized as $u = u_0^m$ and $s = ns_0$, and the resulting wavelets are also discretized as

$$\psi_{m,n}(x) = u_0^{-m/2}\psi\left(\frac{x-ns_0}{u_0^m}\right) \tag{3}$$

where m and n are integer values. The discrete wavelet transform is defined as

$$DWT_f(m,n) = \int_{-\infty}^{\infty} f(x)\psi_{m,n}(x)dx. \tag{4}$$

The matrix of the wavelet coefficients, $CWT_f(u,s)$ or $DWT_f(u,s)$, is called the scalogram which indicates the frequency localization to different scales and time. For its interpretation, the scalogram is charted in a color scale that represents the magnitude of wavelet coefficients. For computing the wavelet coefficients is selected a

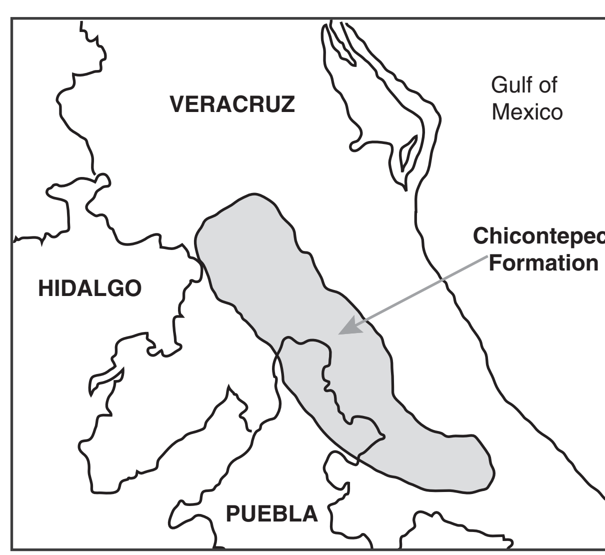

Fig. 2. Schematic map of the localization of Chicontepec formation.