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Geoscientific Instrumentation Methods and Data Systems
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Discussions

Geological Stratigraphy and Spatial Distribution of Microfractures over Costa Rica Convergent Margin, Central America- A Wavelet-Fractal Analysis

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Abstract

Identification of spatial variation of lithology, as a function of position and scale, is very critical job for lithology modelling in industry. Wavelet Transform (WT) is an efficacious and powerful mathematical tool for time (position) and frequency (scale) localization. It has numerous advantages over Fourier Transform (FT) to obtain frequency and time information of a signal. Initially Continuous Wavelet Transform (CWT) is applied on gamma ray logs of two different Well sites (Well-1039 & Well-1043) of Costa Rica Convergent Margin, Central America for identifications of lithofacies distribution and fracture zone later Discrete Wavelet Transform (DWT) applied to DPHI log signals to show its efficiency in discriminating small changes along the rock matrix irrespective of the instantaneous magnitude to represent the fracture contribution from the total porosity recorded. Further the data of the appropriate depths partitioned using above mathematical tools are utilized separately for WBFA. As consequences of CWT operation it is found that there are four major sedimentary layers terminated with a concordant igneous intrusion passing through both the wells. In addition of WBFA analysis, it is clearly understanding that the fractal dimension value is persistent in first sedimentary layers and the last gabbroic sill intrusions. Inconsistent value of fractal dimension is attributed to fracture dominant in intermediate sedimentary layers it is also validate through core analysis. Fractal Dimension values suggest that the sedimentary

environments persisting in that well locations bears abundant shale content and of low energy environments.

Key words: CWT, DWT, Fractal, Costa Rica.

1. Introduction

The nature of any log signal is fluctuating type in accordance to the subsurface geology. A gamma ray log is most vividly used log for lithology identifications. These signals are very noisy in some cases and highly fluctuating in another way. Manual interpretations of such signals are quite difficult and it needs more experience. These difficulties are minimised by kind of wavelet transform method. In our study Continuous Wavelet transform (CWT) is tested on generated synthetic signals and applied to field data. The analysed results prove that the CWT is highly suitable in geophysical log signals whereas conventional Fast Fourier Transform fails in this case because it considers the whole signal in a stationary form. Though Wavelet Transform provides unambiguous results in analysing the noisy and non-stationary signals, its efficiency of extracting the information from the signal was seen through its wavelet coefficients (Hui and Zaixing, 2010) with wavelet scalogram. Number of publication has come to identify the lithofacies/boundary using various mother Wavelet transform and Fourier transform (Chandrasekhar et al., 2012; Coconi et al., 2010; Dashtian, 2011; Javid and Tokhmechi, Mansinha et al.,1997; Mansinha 2003, 2004; Pan et al.,2007, 2012; Pinnegar and Stockwell, 2007; Stockwell et al., 1996; Sahimi and Hashemi, 2001; Tokhmechi et al., 2009a, b; Yue et al., 2004; Zhang et al., 2011;).

In this paper, CWT and Discrete wavelet transform (DWT) are used separately for identifying the lithology using gamma ray log data of well site 1039 and 1043 obtained from Costa Rica Convergent Margin, Central America and computed wavelet scalograms. Moreover, the information of fractures zones is analyzed with DWT using density logs data for both wells that provides well featured whereas the log data doesn't carry information of fracture remains featureless. Afterward, a linear relationship is obtained between the fracture density obtained through DWT and identified fractures from water saturation logs using above methods. Apart from wavelet analysis, one of the approach wavelet based fractal analysis techniques applied to attribute the roughness/smoothness of the fractures. The obtained suggest that wavelet transform acts as a microscope to delineate the high and low frequency hidden in the signal separately, wavelet/holder exponent and fractal dimension are highly useful in identification of lithofacies and spatial distribution of fractures.

2. Mathematical Background

2.1 Wavelet Transform

Wavelet transform is mathematical tool that can be used to analyse both stationary and non-stationary signals (Daubechies 1990, 1992) and expand time series into time frequency space. Therefore, this method can find localized intermittent periodicities. For analysing stationary or non-stationary signal proper mother wavelet has to be substituted and the operation of continuous wavelet transform (CWT) proceeds as the convolution between time series of our interest. The Discrete wavelet transform (DWT) is very useful in case of noisy data it compresses the data by reducing noise and improve the resolution whereas the application of CWT is preferring to extract the lithological feature from data. As it exposes the signal to high and low frequency filters to form approximate and detailed coefficients traces out the abrupt changes in the signal (Figure 8a and 8b). Basically, in geophysical well logs the abrupt change corresponds to its own individual parameter changes which provide us more information about the subsurface stratigraphy. This methodology pertaining to DWT allows us to locate the high frequency changes immersed in the log which cannot be identified manually. For example, gamma ray log is a good lithology indicator but in certain conditions it is highly fluctuating in nature. This nature sometimes perturbs its evaluation. Apart from lithology identification, DWT provides an advantage of analysing the fracture identifications.

2.2Continuous Wavelet Transform

The concept of continuous wavelet transform can be explained by a basic equation given below:

$$W(a,b) = \frac{1}{a^n}\int_{-\infty}^{\infty} f(x)\varphi\left(\frac{x-b}{a}\right)dx \qquad (1)$$

Where, f(t) is the time series of our interest;

φ(t)is the mother wavelet;

a is the scaling parameter otherwise denoted as the Inverse of Frequency;

b is the Translation parameter, which is directly proportional to Time;

n is the Normalising parameter and equal to 1 generally(say).

The variance of Wavelet coefficients follows power law relation with the scale which can be given by a simple equation given below;

$$v = x^h$$

Here v is the variance of wavelet coefficients; x is the scale and h is the holder/wavelet exponent.

Holder/Wavelet exponent provides the measure of roughness/smoothness. If the holder exponent values are high, it accounts for smoothness whereas low values of holder exponent emphasis more roughness. After obtaining the holder exponent it can be substituted in the equation given below to obtain the fractal dimension Value;

$$2D = 5 - h$$

Here, D is the fractal dimension (FD).

2.3 Discrete Wavelet Transform

One- dimensional Discrete Wavelet Transform has been carried down in this task as per the datasets, which are discrete and one dimensional. For the construction of DWT one sets, a = 2^j and b = 2^jk, where j and k are both integers. 1-D DWT is given by the following equation,

$$D_j(k) = 2^{-\frac{j}{2}} \int_{-\infty}^{\infty} f(t)\, \varphi\left(2^{-j}t - k\right) dt \qquad (2)$$

Where f(t) is the time series of our interest; K=1, 2, 3...., n, n being the Discrete data array of maximum Size. Time series of our interest is decomposed to Approximate and Detailed Coefficients providing both lower and higher frequency information respectively.

3.0 Results and Discussions

3.1 Application to Synthetic data

A Synthetic signal is generated with three different frequencies such as 3Hz, 5Hz and 10Hz and analysed by CWT and also applied to synthetic signal added with 25% Gaussian white noise. The result obtained is shown in Figure 1. As the signal is free from noise possessing only its own frequencies the mathematical tools didn't posed any difficulty and the information required are derived without any ambiguity. When the same signal analyzed by the above mentioned techniques after mixing noise, it provides large difference in the results which are shown in Figure 2. The CWT provides an acceptable picture in analysing the non-stationary as well as the same non-stationary signal mixed with noise.CWT not only removes the ambiguity through by forming wavelet modulus maxima but also through its Wavelet Coefficients. Also it provides a picture of the Time-Frequency localisation in interpretable form. An advantage pertaining to wavelet transform is that the Wavelet coefficients records the exact information of the signal even it is noisy. This notion regarding CWT proves it as a good tool for identification of lithology in Well logs. Therefore, this technique can be used in all circumstances to derive the exact information in the Signal.

Mostly, Porosity logs are used for this approach and the fluctuating nature of the porosity logs can be correlated to both Pores distribution and the fracture (major as well as several micro fractures) as well. DWT differentiates both fractures and the characteristics of the pores in the detailed coefficients (Sahimi and Hashemi, 2001). Suppose, the datasets are collected in a fracture less well than the wavelet detail coefficient (WDC) plot will be featureless as given below (left of Figure3) but if the datasets are collected in a fractured well then the WDC plot will be containing highly differentiable features in terms of spikes or local maxima (right of Figure 3). Same log signal is used in the right one but certain data points are removed and replaced. The data points which do replaced pertaining to the uniform distribution constitute both low and high values in comparison with its surrounding data points. DWT differentiates these particular locations by means of a spike irrespective of the magnitude of the data points replaced. DWT exposes the signal to low and high frequency filters produces Detailed and Approximate coefficients respectively.

3.2 Application of Field Data: Costa Rica Convergent Margin, Central America

Costa Rica Convergent Margin in Central America is due to the convergence of Cocos and Caribbean Plates. A seismic migrated section over the region is shown in the Figure 4showing Well sites 1039, 1040 and 1043. Among these wells sites 1039 and 1043 are taken for study whereas the site 1040 is omitted as it is not passing through certain major litho-units. Logs such as gamma ray and density are taken for study and the gamma ray signals exhibiting sharp spikes which are attributed to presence of interbeded ash layers. From the gamma ray log various lithology are identified and correlated with site adjacent to it. Density Logs are used for identification of spatial distribution of fractures along the rock matrix using DWT and WBFA. Core Analysis reports the presence of four sedimentary layers terminated by a concordant Igneous Intrusion Gabbroic Sill. Well site 1039 is taken as the reference and lithology identified through Wavelet Transform are correlated to the site-1043 and the result confirms the subduction zone (Figure 7).

As conventional technique such as Fast Fourier Transform fails in providing the time-frequency localisation. So, the application of wavelet Transform is the only way to find the proper time-frequency localisation. The results obtained from CWT analyzed using log data sets prove the lithological successions. The stratigraphic interfaces occurring in the Well log-1039 (Figure 5) appears in the Well log-1043 (Figure 6) after having disruptions in the middle. From the seismic section it is seen that there are four major lithology running from the Well-1039 to Well-1043 and terminated as Gabbroic Sill. The Well-1040 crossed the above mentioned strata very mildly and it didn’t reach the Concordant intrusive structure as reached by the Wells-1039 and 1043. Therefore, for interpretation point of view only the Wells-1039 and 1043 are used. The major successions mentioned after drilling is that the four sedimentary interfaces followed by a Gabbroic sill. The sedimentary succession obtained underneath the reference site-1039 situated in the Cocos Plate found to occur in the site-1043 without any disruption. It is also noted from the observation made by Eric et al., (2000) as the Cocos Plate subducting under the Caribbean Plate the off scarping of the sediments in the Cocos Plate should occur on the overriding plate but on analysing the chemical composition it was mentioned the sediment lying on the overriding plate was of different composition. This analyses comes in support of the effort of framing the subducting system of Costa Rica using CWT shown in the Figure 7, it is observed that the sedimentary succession in the site-1039 over the subducting Cocos Plate continuing through the site-1043 without any disruption situated over the overriding Caribbean plate. In accordance to the locations of the Wells and the continuity of the sedimentary successions existing in the both sites (1039 and 1043) as traced by the Wavelet scalogram, it is found that the Cocos Plate is subduction under the Caribbean plate. The lithology identified through time and frequency localisation tools are used for the WBFA by taking their data points separately. Table 1 shows the FD values of various lithofacies of both well. From Table 1, we observe that there is transitional change between sandy and Shaly environments on the basis of variation in FD values and this variation corresponds to a gradual transition between different sedimentary environments. Hence, our study suggests that the FD can be used as a well log attribute or even a post-stack seismic attribute for reservoir characteristic (Brown, 2004).

In Table 1, FD values are greater than 1.2 that emphasises the presence of high shale content and of low energy environment in depth range between 210 and 330 and between 315 and 430 as reported the presence of sandstone in well site 1039 and 1043 respectively (Figure 10-11). In spite of the presence of sandstone the fractal dimension values are exceeding 1.2 indicating the dominance of shale content and the values are found to be not consistent from reference site and site 1043. In prior depth ranges, the inconsistency of fractal dimension values are attributed to the presence of fractures from the structural observations obtained in well site but in the above mentioned depth ranges the inconsistency as well as from the holder exponent values it is noted that the roughness exists in the particular lithology. The analysed results are well correlated with the core samples.

7. Conclusions

Lithology identification is a tedious job in well logging and it is the most important one for reservoir characterisation. To identify Presence of structural feature such as fracture by quick look interpretation methods is very difficult using well log data. Formation micro imager (FMI) log often used to identify it is very expensive. Thus methodology used for lithology and fracture identification using wavelet transform and wavelet based fractal analysis using holder exponent can be a useful stuff to extract the different lithological feature as well as stratigraphy feature.

For structural feature identification from various lithologies holder exponent and fractal dimension values can be utilised and in the presence of some extra information as that of the structural observations from well sites the results can be more promising. In order to avoid the assistance of extra information more datasets are needed from the same area so that on application of WBFA on various lithologies passing through the area provides concrete idea on lithology and Structural features using holder exponent and fractal dimension values.

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Figure and Table Captions

Figure 1: Shows the Continuous Wavelet Transform (CWT) using a synthetic time series data.

Figure 2: Shows the Continuous Wavelet Transform (CWT) of a synthetic noisy time series data,

Figure 3: (a) Shows Discrete wavelet Transform (DWT) using synthetic data and original signal and its DWC-1 below it, (b) synthetic data and original signal edited at certain points and it's DWC-1 below it.

Figure 4: Shows the seismic migrated section showing the Wells (after Erik et al, 2000)

Figure 5: showing Continuous Wavelet Transform (CWT) using gamma ray signal and the Wavelet Coefficient at an altitude-32 of the gamma ray log of the Well location-1039

Figures 6: Showing Continuous Wavelet Transform (CWT) using gamma ray signal and the Wavelet Coefficient at an altitude-32 of the gamma ray signal of the Well location-1043

Figure 7: Represents the lithology identification using the gamma ray log of the Well site 1039 and 1043 by the lines drawn on the scalogram and it represents the subduction zone in the areas obtained from the seismic migrated section.

Figure 8: (a) Shows the discrete detailed and approximate coefficients and the spikes represents the possible fractures at well location 1039, (b) shows the Discrete detailed and Approximate coefficients and the spikes represents the possible fractures at well location 1043

Figure 9: shows the scale of interest shows variance of wavelet coefficients versus scale of gamma ray of well site 1039 and 1043

Figure 10: Shows variance of Wavelet coefficients versus scale of density log of well site-1039 and 1043 which shows consistent holder exponent and fractal dimension values indicating that wells contains similar sedimentary environment.

Figure 11: shows the FD values of both well sites of 1039 and 1043.

Table 1: Shows the FD values of the appropriate lithology identified and the circled depth ranging and its appropriate fractal dimension values showing deviation of the vales from the reference site 1039.

Table 2: Shows the ranges of fractal dimension values.

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Figure 1

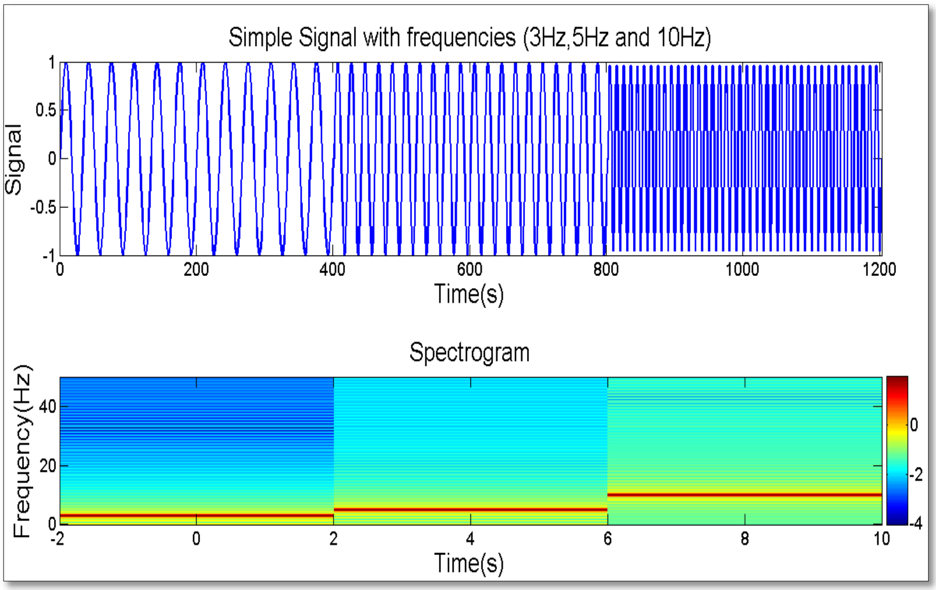
Simple Signal with frequencies (3Hz,5Hz and 10Hz)
Signal
1
0.5
0
-0.5
-1
0
200
400
600
800
1000
1200
Time(s)
Spectrogram
Frequency(Hz)
40
20
0
-2
0
2
4
6
8
10
Time(s)
0
-2
-4

Figure 2

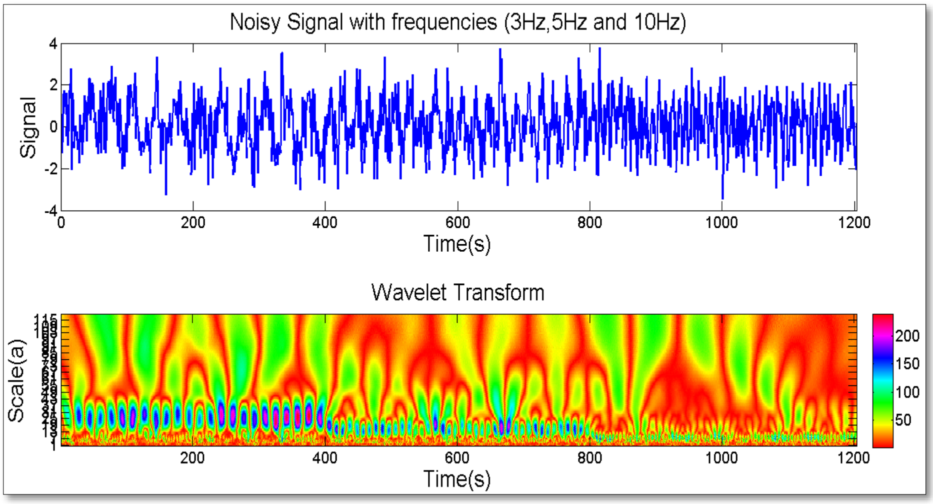
Noisy Signal with frequencies (3Hz,5Hz and 10Hz)
Signal
Time(s)
Wavelet Transform
Scale(a)
Time(s)
200
150
100
50

Figure 3(a)

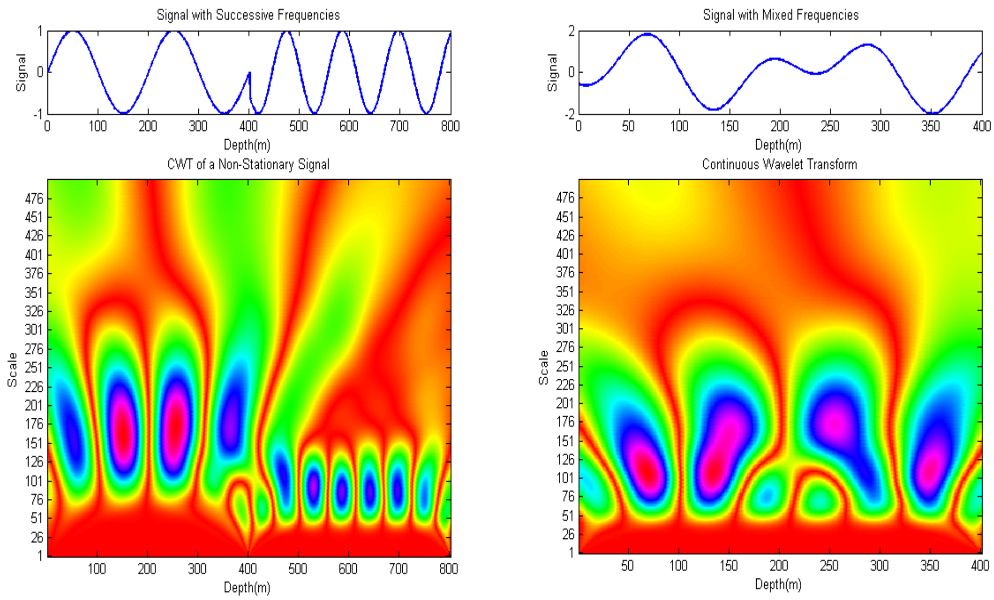
Signal with Successive Frequencies
Signal
Depth(m)
CWT of a Non-Stationary Signal
Scale
Depth(m)
Signal with Mixed Frequencies
Signal
Depth(m)
Continuous Wavelet Transform
Scale
Depth(m)

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Figure 3(b)

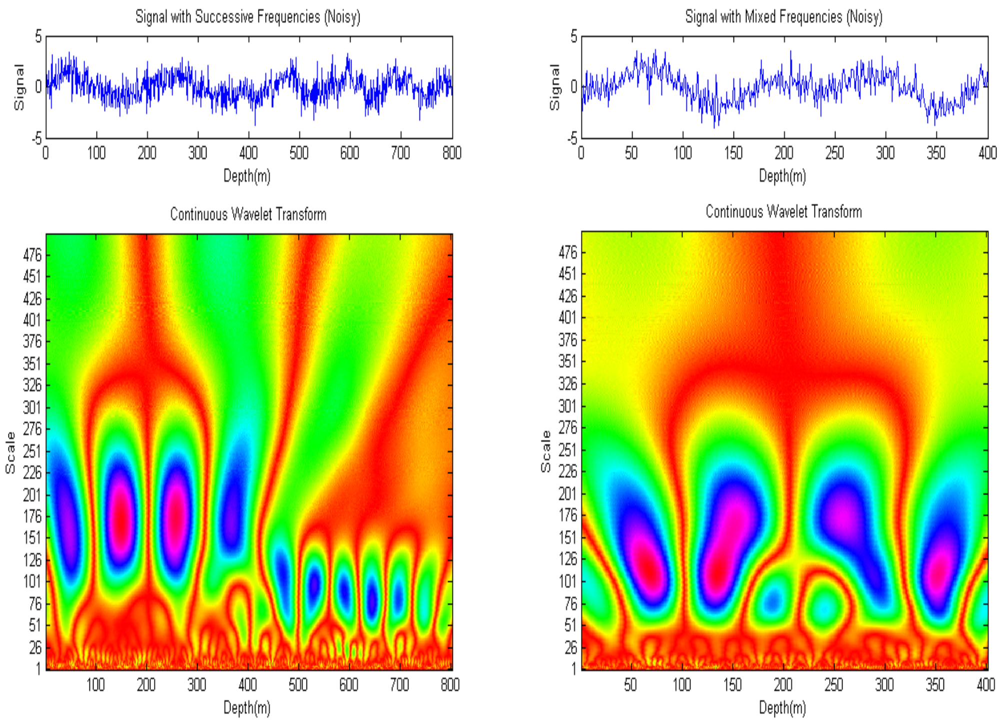

Figure 4

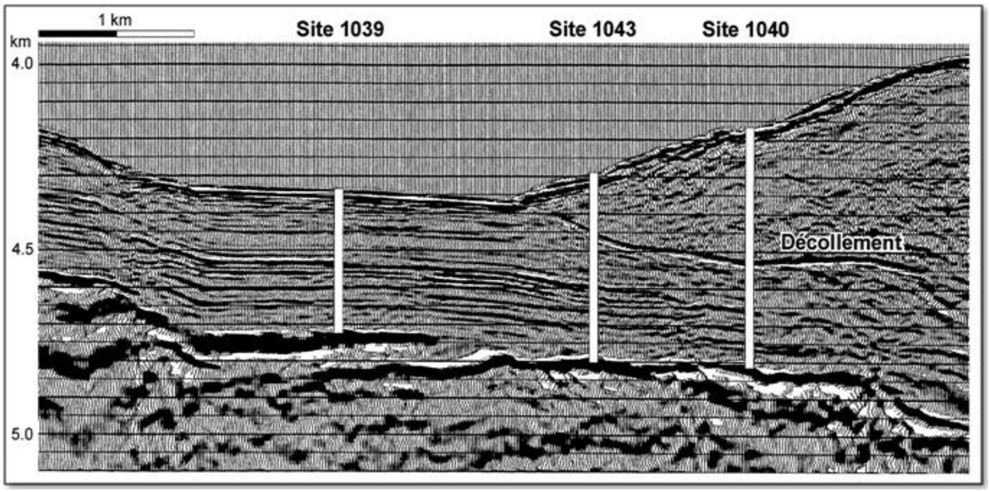

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Figure 5

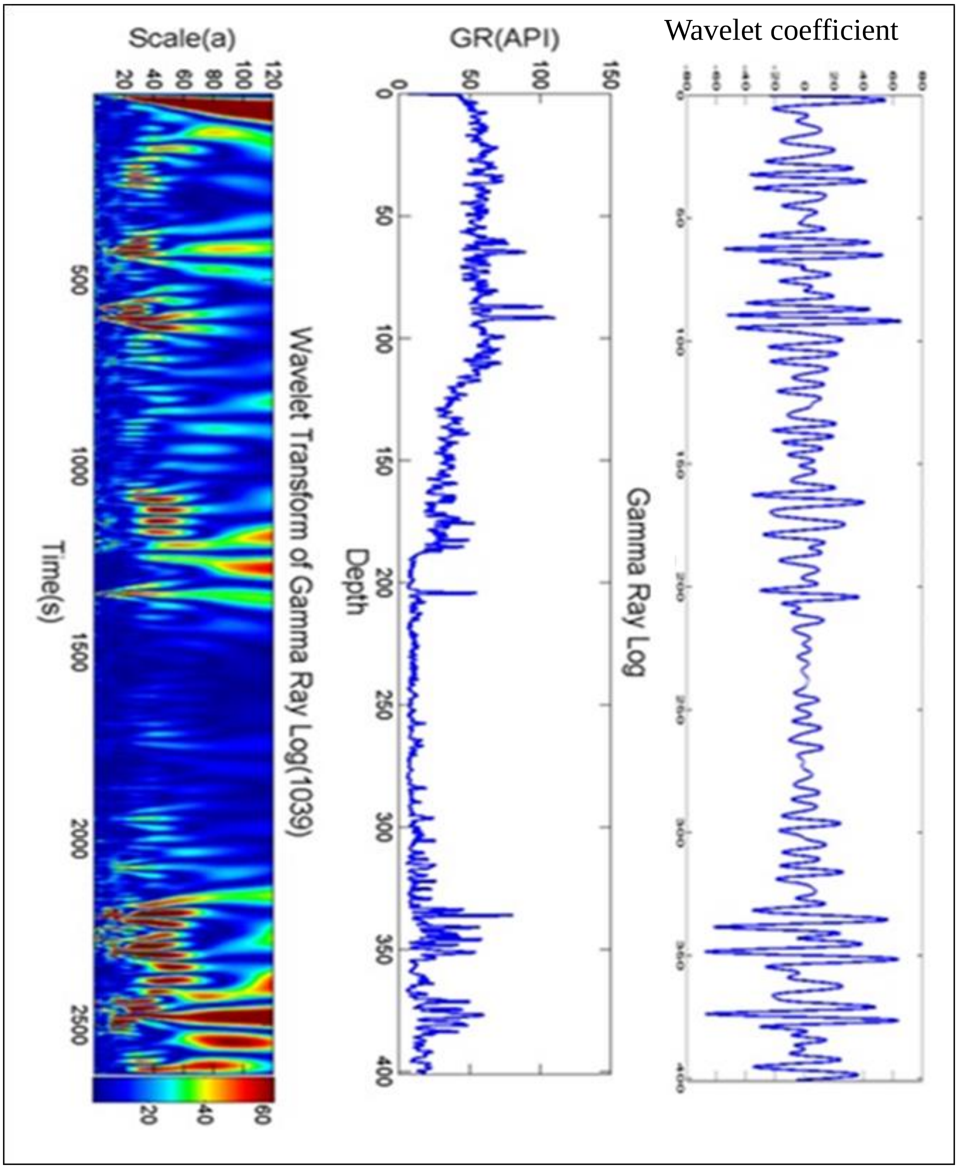

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Figure 6

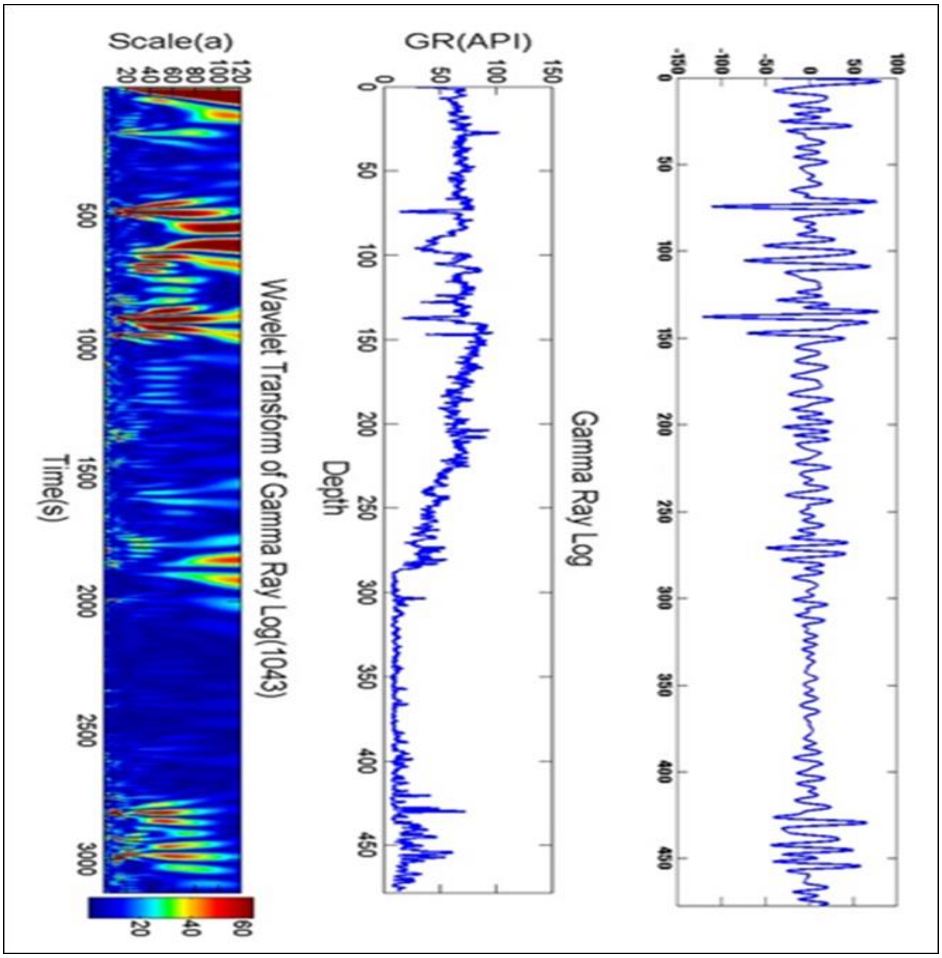

Figure 7

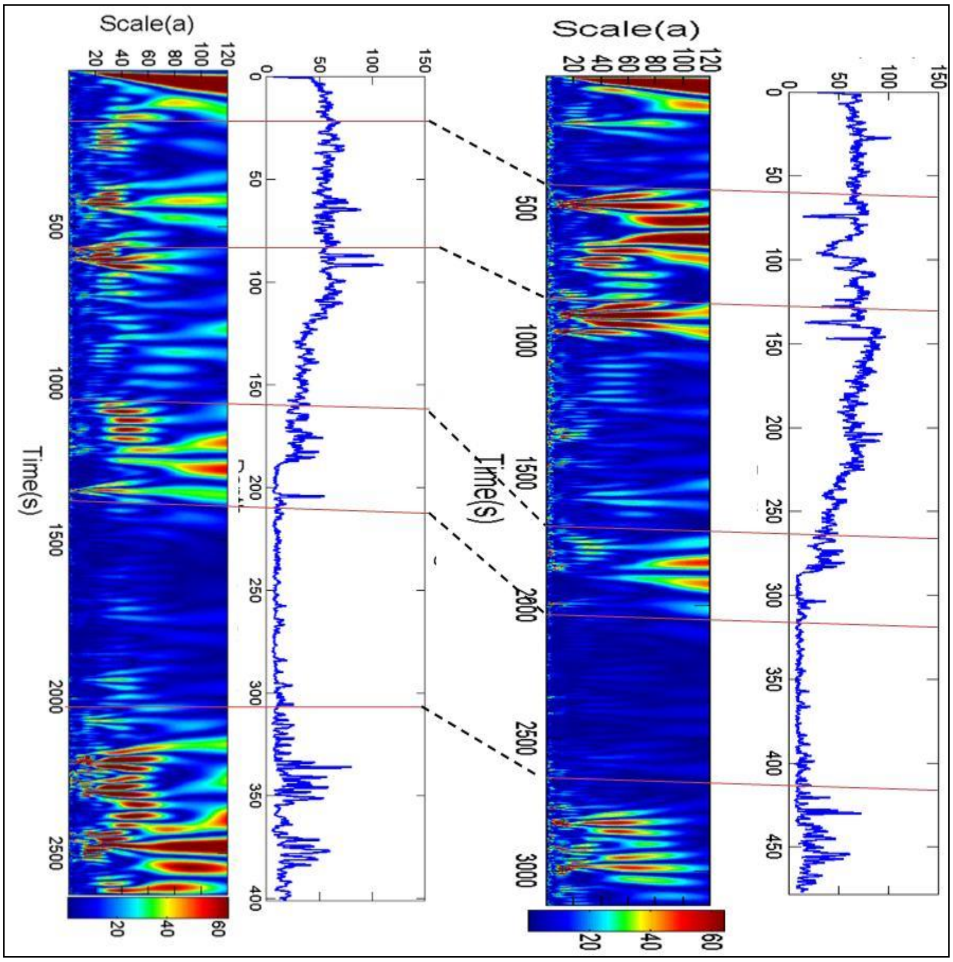

Figure 8

(a) (b)

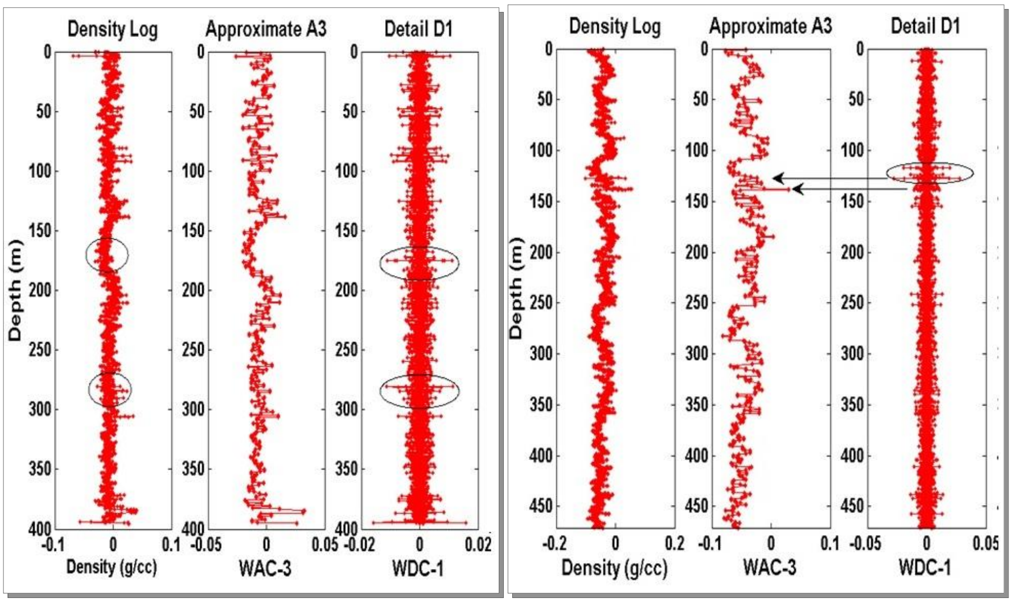
Density Log
Approximate A3
Detail D1
Depth (m)
Density (g/cc)
WAC-3
WDC-1

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Figure 9

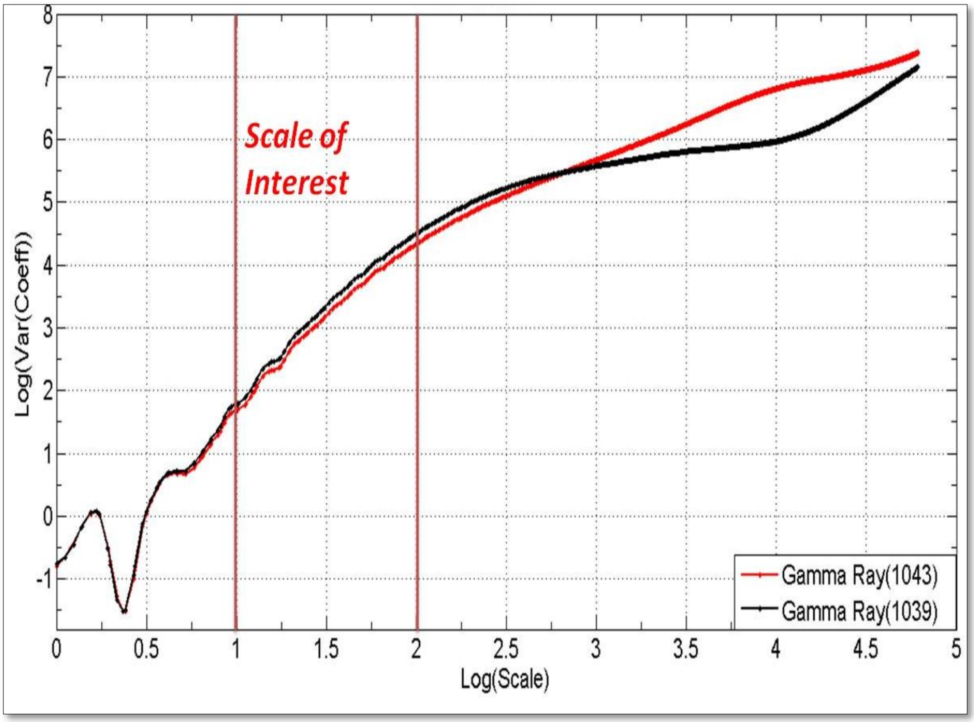

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Figure 10

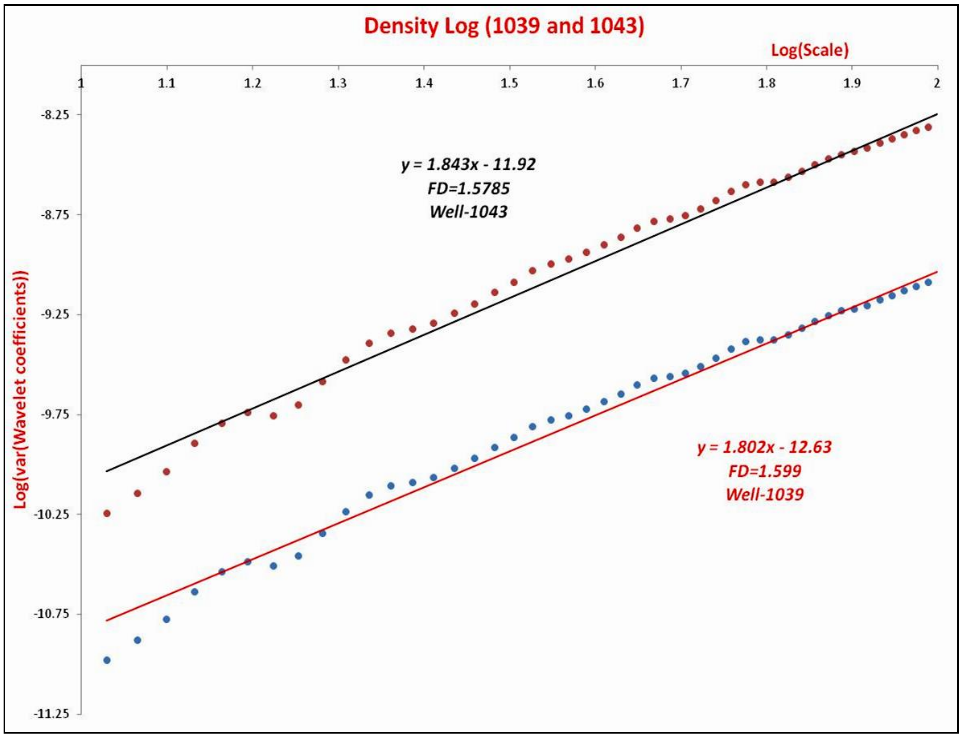

Figure 11

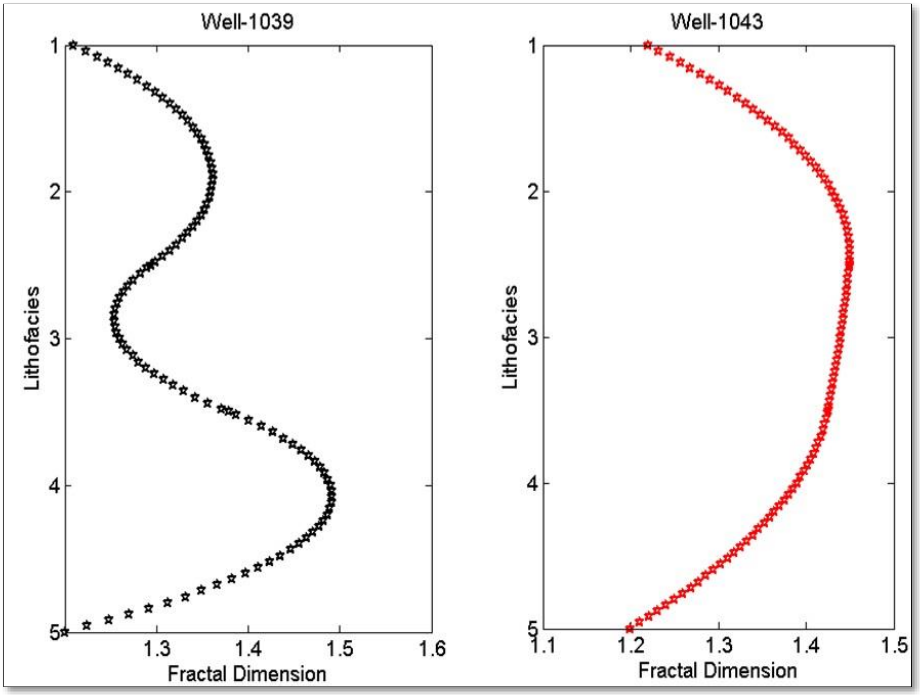
Well-1039
Lithofacies
1
2
3
4
5
1.3
1.4
1.5
1.6
Fractal Dimension
Well-1043
Lithofacies
1
2
3
4
5
1.1
1.2
1.3
1.4
1.5
Fractal Dimension

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Table 1

Lithofacies	Depth range(meter)		Fractal Dimension	
	Well-1039	Well-1043	Well-1039	Well-1043
Shale with inter-bedded ash	20-80	60-130	1.21	1.22
Shaly sandstone	80-160	130-26	1.36	1.43
Sandy shale with inter-bedded ash	160-210	260-315	1.26	1.44
sandstone	210-330	315-430	1.49	1.39
Gabbroic Sill	330-400	430-450	1.20	1.20

Table 2

Fractal Dimension	Interpretation
< 0.9	High sand content and high energy environment
0.9 to 1.2	Inter-bedded sand and shale
> 1.2	High shale content and low energy environment