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MODELING AND CLASSIFICATION OF LITHOFACIES USING THE CONTINUOUS WAVELET TRANSFORM AND NEURAL NETWORK: A CASE STUDY FROM THE BERKINE BASIN (ALGERIA).

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ABSTRACT

We use a neural statistical method combined with the multiscale wavelet analysis for lithofacies classification from well-logs data. This approach has been applied to constrain the lithofacies boundaries by parameterezing five sets of well log data which are density, neutron porosity, gamma ray, sonic velocity and photoelectric cross section, obtained from two boreholes located in the Berkine sedimentary basin. This basin is located, in the North-East of the Saharan Platform. It is considered as a vast Palaeozoic depression in which the crystalline basement is covered by an important sedimentary series and presents a considerable interest in terms of oil.

First, we analyze the fluctuations of these five sets of well log data using the continuous wavelet transform, power law exponents are then derived for the 2838.5-3082 m depth interval. The power law exponent allows to establish the Hölder exponent of each well-log data.Second, a Self Organizing Map (SOM) neural network model was generated in an unsupervised feed-forward mode for training the set of Hölder exponents. We can then infer the lithology sampled by the drill in two different ways: firstly by direct measurements and secondly by their corresponding Hölder exponents.

The current data analysis suggests that this approach is able to emulate the pattern of all five sets of borehole data and correctly identify lithofacies. Indeed, we observe, that the spectral exponents derived logs are more efficient than the direct downhole measurements. Moreover, the results demonstrate that our approach presents a robust and powerful tool for the classification of complex lithofacies successions from the sedimentary borehole log data. This method may provide useful guide/information for understanding the petrophysical properties and structural discontinuities in other areas.

Keywords - Well logging - Multiscale analysis - Hölder exponent - Self Organizing Map - Lithofacies.

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MODÉLISATION ET CLASSIFICATION DE LITHOFACIÈS PAR TRANSFORMÉE EN ONDELETTES CONTINUES ET RÉSEAUX NEURONAUX : CAS DE LA PROVINCE TRIASIQUE DE BERKINE(ALGÉRIE).

RÉSUMÉ

Dans cette contribution, il est utilisé la combinaison des techniques des réseaux de neurones et de l'analyse multi-échelles, basée sur la transformée en ondelettes continue, pour la classification des lithofaciès des enregistrements de diagraphies.

Cette approche a été appliquée pour prédire les limites des lithofaciès par paramétrisation de cinq enregistrements de diagraphies. Il s'agit de la densité globale ρ_b (g/cc), de la porosité neutron Φ_N (%), du rayonnement γ-naturel GR (API), du temps de parcours Δt (μs/ft) et du coefficient d'absorption photoélectrique Pe (Barns/e-). Les logs de diagraphies proviennent de deux sondages pétroliers du bassin de Berkine.

Ce bassin est situé au NE de la Plate forme Saharienne. Il est constitué d'une vaste dépression paléozoïque où le socle cristallin est recouvert par une importante série sédimentaire. Dans cette dernière, plusieurs niveaux argilo-gréseux sont potentiellement riches en hydrocarbures.

L'analyse des déflections de ces enregistrements de diagraphies a permis la définition de la composante en loi d'échelle de l'intervalle de profondeur 2838.5m - 3082.0 m, en utilisant la transformée en ondelettes continues.

Pour chaque diagraphie utilisée, une loi de puissance est appliquée afin d'établir une série d'exposants de Hölder. A partir d'un apprentissage non supervisée de cette série d'exposants de Hölder, une carte auto-organisée de Kohonen (SOM) a été générée.

La lithologie a été alors déduite de deux manières différentes. La première a exploité directement les enregistrements de diagraphies. La seconde par contre, s'est basée sur les séries d'exposants de Hölder, correspondantes aux diagraphies utilisées.

L'analyse des résultats montre que cette approche mathématique est en mesure d'identifier correctement les lithofaciès des cinq diagraphies exploitées. En effet, on remarque que les exposants spectraux, calculés à partir des logs de diagraphies, renseignent efficacement sur les interfaces de couches traversées par les sondages étudiés.

En outre, les résultats obtenus permettent de dire que cette technique constitue un outil puissant et robuste pour la classification des lithofaciès complexes à partir des logs de diagraphies. Elle offre un guide/information utile à la compréhension des variations possibles des propriétés pétrophysiques et des discontinuités structurales dans d'autres régions.

Mots-clés - Diagraphies - Analyse multi-échelles - Exposant de Hölder - Carte auto-organisée- Lithofaciès.

1. INTRODUCTION

One of the main goals of geophysical studies is to apply suitable mathematical and statistical techniques to extract information about the subsurface properties. Well logs are largely used for characterizing reservoirs in sedimentary rocks. In fact, it is one of the most important tools for hydrocarbon research for oil companies. Several parameters of the rocks can be analysed and interpreted in term of lithology, porosity, density, resistivity, salinity as well as the quantity and the kind of fluids within the pores.

Geophysical well-logs often show a complex behavior which seems to suggest a fractal nature (Pilkington & Tudoeschuck, 1991; Wu and *al*., 1994; Turcotte, 1997). They are geometrical objects exhibiting an irregular structure at any scale. In fact, classifying lithofacies boundary from borehole data is a complex and nonlinear problem. This is due to the fact that several factors, such as pore fluid, effective pressure, fluid saturation, pore shape, etc. affect the well log signals and thereby limit the applicability of linear mathematical techniques. To classify lithofacies units, it is, therefore, necessary to search for a suitable nonlinear method, which could evade these problems.

The scale invariance of properties has led to the well known concept of fractals (Mandelbrot, 1982). It is commonly observed that well log measurements exhibit scaling properties, and are usually described and modelled as fractional Brownian motions (Pilkington and Tudoeschuck , 1991; Wu and *al*., 1994; Kneib 1995; Bean, 1996; Holliger, 1996; Turcotte, 1997; Shiomi and *al*., 1997; Dolan and *al.,* 1998; Li, 2003). In previous works (Zaourar and *al*., 2006a, 2006b), we have shown that well logs fluctuations in oil exploration display scaling behaviour that has been modelled as self-affine fractal processes. They are therefore considered as fractional Brownian motion (fBm), characterized by a fractal $k^{-\beta}$ power spectrum model where k is the wave number and β is related to the Hurst parameter (Herrmann,1997). Theses processes are monofractal whose complexity is defined by a single global coefficient, the Hurst parameter H, which is closely related to the Hölder degree regularity. Thus, characterizing scaling behaviour amounts to estimating some power law exponents.

Petrophysical properties and classification of lithofacies boundaries using the geophysical well log data is quite important for the oil exploration. Multivariate statistical methods such as principle component and cluster analyses and discriminant function analysis have regularly been used for the study of borehole data. These techniques are, however, semi-automated and require a large amount of data, which are costly and not easily available every time.

The modern data modelling approach based on the Artificial Neural Network (ANN) techniques is inherently nonlinear and completely data-driven requiring no initial model and hence, provide an effective alternative approach to deal with such a complex and nonlinear geophysical problem. Some researchers have been engaged in classifying lithofacies units from the recorded well logs data. They have recently employed statistical and ANN methods (Briqueu and *al*., 2002; Chikhi, 2004. More recently, Zaourar and *al*., 2006b presented the results that allow to construct the lithofacies of the well logs obtained by the French agency ANDRA in the Gard (France) from compacted, cemented and anhydrous siliciclastic unit, using an unsupervised Kohonen's self-organizing neural network combined with a multiscale wavelet analysis.

In this work, we apply the similar approach for reservoir characterization and statistical classification of data measured in sedimentary basins. We analyse several petrophysical properties recorded in two boreholes, Sif Fatima2 and Sif-Fatim3 located in the Berkine Basin in the North-East of the Saharan Platform (Algeria). This basin is considered as a vast Palaeozoic depression in which the crystalline basement is covered by an important sedimentary series. Lithologically, the explored geological unit at the drill site consists of four main facies units: clay, sandstone and alternations of clayey sandstone and Sandy Clay (Zeroug and *al.*, 2007).

A fractal model is assumed for the logs and they are analysed by the Continuous Wavelet Transform (CWT) which maps the measured logs to profiles of Hölder exponents. We use the estimated wavelet Hölder exponents rather than the raw data measurements to enhance a classification process initiated by a self organizing map of Kohonen procedure.

In this paper, we first present a short mathematical description to show that the CWT is the suitable tool used to analyse concept of a self affine process. Second, we describe the neural network method, particularly, the Kohonen's Self Organizing Map (SOM) and its derived processing algorithm. Finally, we show that the use of these combined techniques provides a powerful tool for lithofacies classification.

2. WAVELET ANALYSIS OF SCALING PROCESSES

Here, we review some of the important properties of wavelets, without any attempt at being complete. What makes this transform special is that the set of basis functions, known as wavelets, are chosen to be well-localized (have compact support) both in space and frequency (Arnéodo and *al.*, 1988; Arnéodo and Backy, 1995). Thus, one has some kind of "dual-localization" of the wavelets. This contrasts the situation met for the Fourier Transform where one only has "mono-localization", meaning that localization in both position and frequency simultaneously is not possible.

The CWT of a function s(z) is given by Grossmann and Morlet (1985) as:

$$C_s(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} s(z)\psi^*(z)\,dz \qquad (1)$$

Each family test function is derived from a single function defined to as the analyzing wavelet according to Torrésiani (1995) :

$$\psi_{a,b}(z)=\psi\left(\frac{z-b}{a}\right) \qquad (2)$$

Where $a\in R^{+*}$ is a scale parameter, $b\in R$ is the translation and ψ^* is the complex conjugate of ψ. The analyzing function is generally chosen to be well localized in space (or time) and wave number. Usually, $\psi(z)$ is only required to be of zero mean, but for the particular purpose of multiscale analysis $\psi(z)$ is also required to be orthogonal to some low order polynomials, up to the degree n−1, i.e., to have *n* vanishing moments :

$$\int_{-\infty}^{+\infty} z^n\psi(z)\,dz = 0 \quad for \;\; 0\le n\le p-1 \qquad (3)$$

According to equation (3), p order moment of the wavelet coefficients at scale a reproduce the scaling properties of the processes. Thus, while filtering out the trends, the wavelet transform reveals the local characteristics of a signal and more precisely its singularities.

It can be shown that the wavelet transform can reveal the local characteristics of s at a point z_0. More precisely, we have the following power-law relation (Hermann, 1997; Audit and *al*., 2002):

$$\left|C_s(a, z_0)\right| \approx a^{h(zo)} \text{ ,when } \quad a \to 0^+ \qquad (4)$$

where h is the Hölder exponent (or singularity strength). The Hölder exponent can be understood as a global indicator of the local differentiability of a function s.

The scaling parameter (the so-called Hurst exponent) estimated when analysing process by using Fourier Transform (Zaourar and *al*., 2006a) is a global measure of self-affine process, while the singularity strength h can be considered as a local version (i.e. it describes 'local similarities') of the Hurst exponent. In the case of monofractal signals, which are characterized by the same singularity strength everywhere ($h(z)$ = constant), the Hurst exponent equals h. Depending on the value of h, the input signal could be long-range correlated ($h > 0.5$), uncorrelated ($h = 0.5$) or anticorrelated ($h < 0.5$).

3. NEURAL NETWORK METHOD

The Artificial Neural Network(ANN), based on approaches, has proved to be one of the robust and cost-effective alternative means to successfully resolve the lithofacies boundaries from well log data (Gottlib-Zeh and *al*., 1999; Briqueu and *al*., 2002; Zaourar and *al*., 2006b). The method has its inherent learning ability to map some relations between input and output space, even if there is no explicit a priori operator linking the measured lithofacies properties to the well log response.

3.1. Self Organizing Map of Kohonen

A Self Organizing neural network, or SOM, is a collection of n reference vectors organised in a neighbourhood network, and they have the same dimension as the input vectors (Kohonen, 1998). Neighbourhood function is usually given in terms of a two-dimensional neighbourhood matrix {W(i,j)}. In a two-dimensional map, each node has the same neighbourhood radius, which decreases linearly to zero during the self-organizing process. The conventional Euclidian distance is used to determine the best-matching unit (so called 'winner') {W(iw, jw)} on a map for the input vector {X). Kohonen's SOMs are a type of unsupervised learning. The goal is to discover some underlying structure of the data. Kohonen's SOM is called a topology-preserving map because there is a topological structure imposed on the nodes in the network. A topological map is simply a mapping that preserves neighbourhood relations. In the nets we have studied so far, we have ignored the geometrical arrangements of output nodes. Each node in a given layer has been identical in that each is connected with all of the nodes in the upper and/or lower layer. In the brain, neurons tend to cluster in groups. The connections within the group are much greater than the connections with the neurons outside of the group. Kohonen's network tries to mimic this in a simple way. The algorithm for SOM can be summarized as follows (See fig.1):

- assume output nodes are connected in an array (usually 1 or 2 dimensional);

- assume that the network is fully connected (i.e. all nodes in the input layer are connected to all nodes in the output layer). Use the competitive learning algorithm as follows:

- randomly choose an input vector x;

- determine the "winning" output node i, where W_i is the weight vector connecting the inputs to output node i. Note the above equation is equivalent to W_i x ≥ W_k x only if the weights are normalized;

$$\left|W_i - X\right| \leq \left|W_k - X\right| \ldots\ldots\ldots\ldots\ldots\ldots\ldots \forall k$$

- given the winning node i, the weight update is.

$$W_k(new) = W_k(old) + X(i,k) \times (X - W_k)$$

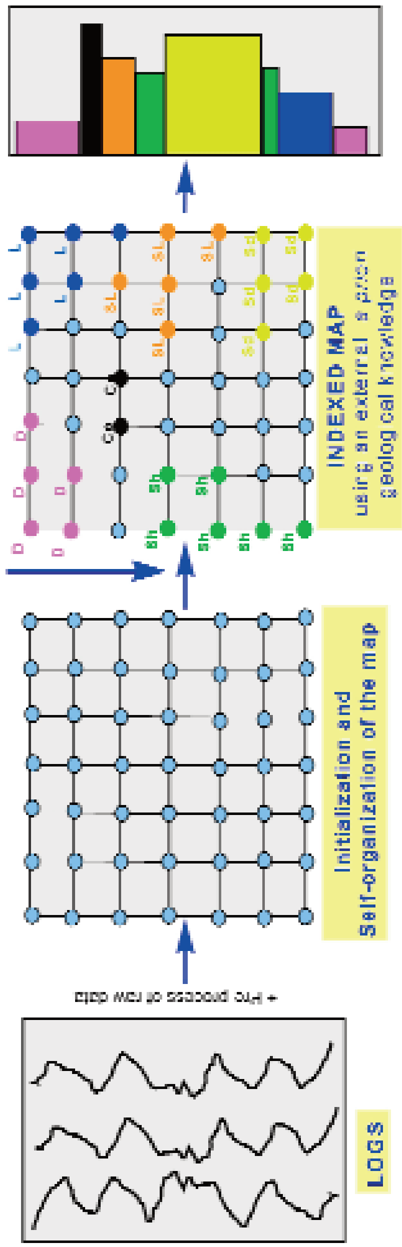

Fig.1 - Schematic illustration of the Kohonen's Self-Organizing Map principle

Schéma montrant le principe de la carte auto-organisée de Kohonen

Where $X(i,k)$ is called the neighborhood function that has value 1 when i=k and falls off with the distance $|r_k - r_i|$ between units i and k in the output array. Thus, units close to the winner as well as the winner itself, have their weights updated appreciably. Weights associated with far away output nodes do not change significantly. It is here that the topological information is supplied. Nearby units receive similar updates and thus end up responding to nearby input patterns. The above rule drags the weight vector and the weights of nearby units towards the input x.

Example of the neighbourhood function is given by the following relation

$$X(i,k) = e^{\left(-|r_k - r_i|^2\right)/(\sigma)^2}$$

Where σ^2 is the width parameter that can gradually be decreased as a function of time.

4. WELL LOGS MEASUREMENTS

4.1. Geological setting

South of the Alpine Algeria, the Saharan Platform is extended on a vast area of over 2 million km^2. On a Pan-African substratum, most of its history is Hercynian with basins separated by high zones, synclines, among them that of Illizi-Berkine (see fig. 2.a).

The Syncline of Illizi-Berkine occupies the North-Eastern part over more than 400 km^2. In this basin, "another basin'', called the Triassic Province, was superimposed during the Mesozoic.

Some structural features delimit the Berkine area :

- in the North, the Djeffara ridge and the Sidi Touil ridge;

- in the West, The bottom-up El Biod - Hassi Messaoud;

- in the South, the Ahara ridge and the Zeghar-Gargaf ridge;

- in the East, the Syrte Basin in Libya.

Filling :

The filling has Paleozoic sediment accumulation (4000 to 5000 m) mainly sandy clay of lower Palaeozoic subsequently admitting some levels of carbonates and evaporites.

The Mesozoic (Triassic-Upper Cretaceous) is not very thick and uncomformably overlaying the previous deposits; it is more or less eroded, according to regions.

The Triassic outcrops very little (In Aménas region) but it is very thoroughly developed in depth and is recognized by many petroleum surveys. It is not very thick (50 to 100 m) and is characterized by continental and varied sedimentation (fluvial, floodplain, eolian, sabkha, playa, volcanism at various epochs). The sedimentary bodies thus generated are discontinuous with lateral passages of facies.

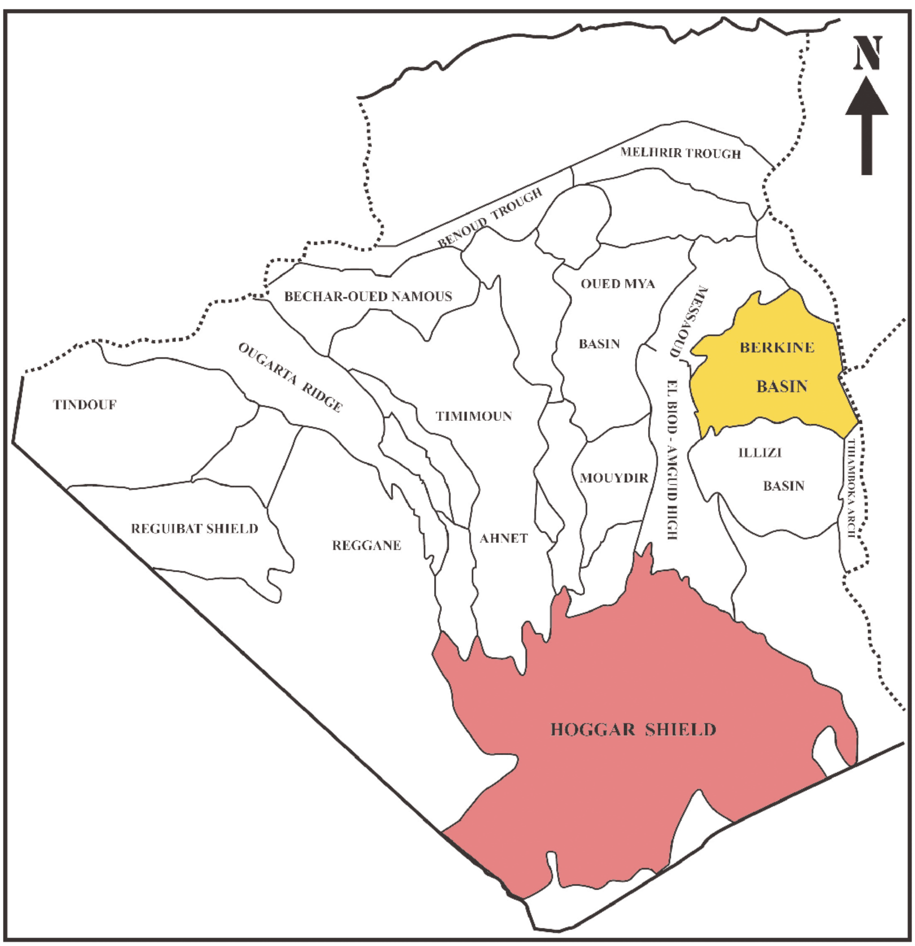

Fig. 2a - Geographic location of the Berkine Basin.

Situation géographique du bassin de Berkine

This sedimentation is interrupted by quiet periods during which paleosoils (complex and varied crusts) develop at the origin of discontinuities

In the Triassic, petroleum geologists distinguish a number of lithological units (fig 2b, table I) :

- Lower Triassic shaly sandstones (TAGI);

- Triassic carbonates and their equivalents;

- Upper Triassic shaly sandstones (TAGS).

Ages given on the basis of palynology (Achab, 1970) are of the Upper Triassic.

At the Berkine regional level, three sets are defined: the lower series, the intermediate series and the upper series (T1, T2).

In another approach, the paleosoils are used to characterize the formation of members (Nedjari and Delfaud, 2002).

This alternative approach led to subdivide the Triassic into four formations (I, II, III, IV) attributed mainly to the Upper Triassic and probably concerning the formation I at the end of the middle Triassic(see fig. 2c).

These formations are based on an alteration profile and regolith developed during a passive phase of the Lower and Middle Triassic pro parte.

4.2. Data description

The physical properties that we analyse were recorded in situ in both Sif Fatima 2 and Sif Fatima 3 boreholes. They include Gamma Ray (GR), Bulk density (RHOB), Photoelectric

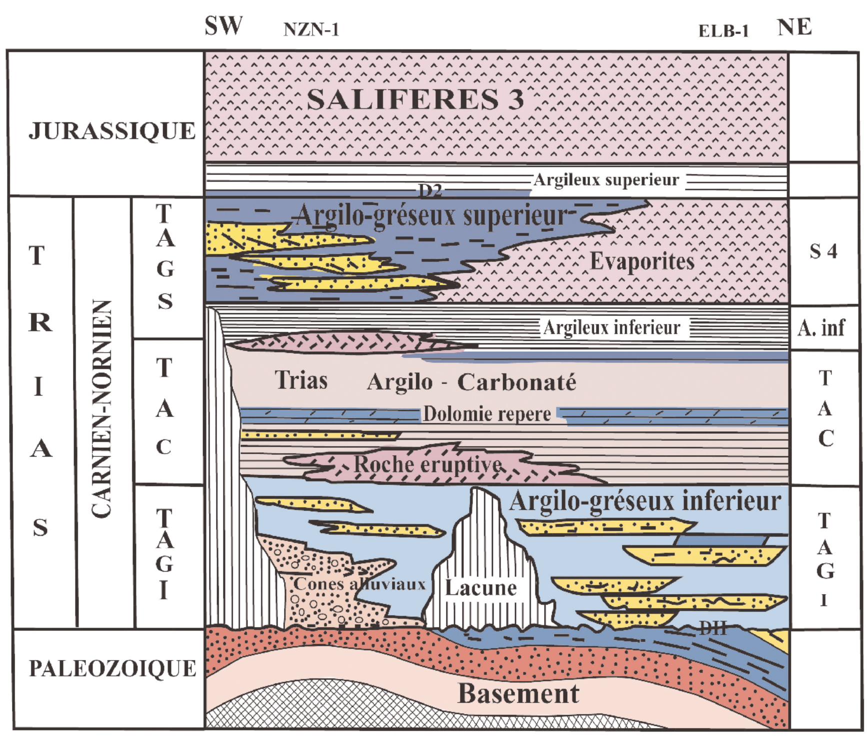

Fig. 2b - Synthetic stratigraphic column of the Trias

Colonne stratigraphique synthétique du Trias

Table I - Trias nomenclature and subdivision used in Algeria (modified by Hamouche , 2006)

Nomenclature et subdivision du Trias utilisées en Algérie (modifiées par Hamouche ,2006)

ALGERIE										
ETAGE		DATATIONS		HASSI R-MEL	OUED MYA	ERG ORIGINAL BASSIN DE BERKINE (BORMA)	GASSI TOUIL RHOUDRE NOUSS (SW DU BASSIN DE BERKINE)	ZARZAITINE		
		PATYNOLOGIE (ZONE) ACHAB 1970	AUTRES CHATEUNEUF 1978					EFFEUREMENT (BEUSSON G.1970 , BOUDJEMA A.1987 (LEP / SONATRACH 1998)		EFFEUREMENT (JALIL KE 2000)
LIAS	HETTAANGIEN	Q	Q	SALIFERE	SALIFERE	SALIFERE	SALIFERE OGIGINAUX	ZARZAITINE SUPERIEUR		ZARZAITINE SUPERIEUR
TRIAS SUPERIEUR	RHETIEN A NORIEN - CARNIEN SUPERIEUR	P3	P3	ARGILO SALIFERE	ARGILO SALIFERE	ARGILO SALIFERE S4	ARGILO-GRESEUX SUPERIEUR	MEMBRE SUPERIEUR	ZARZAITINE INFERIEUR	ZARZAITINE INFERIEUR MEMBRE SUPERIEUR
		AZOIQUE	P2	C	T2	ARGILO CARBONATE	ARGILO CARBONATE	MEMBRE MEDIAN		
				B	T1		GRESEUX INTERMEDIAIRE	MEMBRE INFERIEUR		
		P2	P1 SUP	A						
	CARNIEN SUPERIEUR	P1	P1 SUP	SERIE INFERIEUR	SERIE INFERIEUR	ARGILO GRESEUX INFRIEUR TAGI	ARGILO GRESEUX INFRIEUR TAGI			
TRIAS MOYEN	LADINIEN								ZARZAITINE INFERIEUR Membre inferieur	
	ANISIEN									
TRIAS INFERIEURR	SCYTHIEN SUP									
PERMIEN										

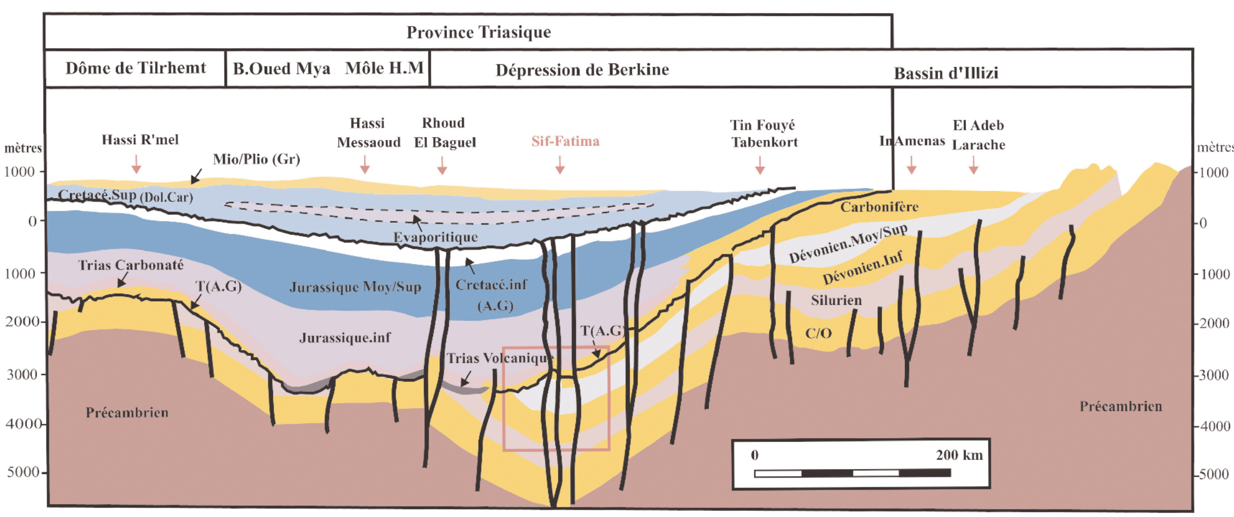

Fig. 2c - Schematic scratch shows :
- The basins geometry in the Oriental set of the Saharan Platform
- Deposits age of the sets of the basins and the lithostratigraphy of the Triassic province

Coupe Schématique montrant :
- La géométrie des bassins dans l'ensemble orientale de la Plate Forme Saharienne
- L'âge des dépôts de l'ensemble des bassins et la lithostratigraphie de la province triasique

cross section (PEF), Neutron porosity (NPHI), and Sonic P wave velocity (Vp).

Let us describe briefly the different measured parameters :

- the Gamma ray log (GR) : the unit is usually given in API (American Petroleum Institute), it measures the radioactivity of rocks and it is used mainly for (1) differentiation between clean zones and clayey zones (2) estimation of the percentage of clay in the rocks;

- the Bulk density (RHOB) : the unit is g/cc (Gramm per cubic centimetre), it measures the bulk density of rocks, by measuring the scattered rays following the bombardment of medium with medium to high energy gamma rays. The most frequently measured densities vary between 2 and 3 g/cc. It is mainly used for the determination of porosity in zones of hydrocarbons or in geological formations containing the clay and, in combination with Neutron; it is used for differentiation between liquids and gases;

- the photoelectric cross section (PEF): when the energy of the Gamma ray bombardment is smaller than 0.1 Mev , the measured interaction is named the photoelectric cross section , the unit is (B/E);

- the Sonic log (Dt) : the unit is μs/ft (microsecond/foot), it measures the variation of the slowness of acoustic wave propagation according to the depth. It must be done in "open" hole that means before the pose of the protective intubation. It is mainly used for the determination of porosity in non-clayey formation and for the identification of lithology. Note that in this paper we used the velocity of the propagation of the P wave(Vp) which is derived from Dt. The unit of Vp is then given in S.I. (m/s);

- the Neutron Porosity (NPHI): it measures the rock's reaction to a very fast neutron bombardment. NPHI is dimensionless. The recorded parameter is an index of hydrogen for a given formation of lithology. It is mainly used for lithology identification and porosity evaluation.

For both Sif Fatima 2 and Sif Fatima 3 boreholes, we consider only the depth interval [2838.5, 3082 m] which corresponds to the main reservoir. The sampling depth rate is 0.1524 m for Sif Fatima 2 and 0.5 m for Sif Fatima 3.

4.3. Preliminary interpretation of natural Gamma Ray well-log

A preliminary raw lithofacies classification based on the natural gamma radioactivity well-log data was made. First, recall that the maximum value GRmax of the data is considered as a full clay concentration while the minimum value GRmin represents the full sandstone concentration. The mean value $(GR_{max}+GR_{min})/2$ will then represent the threshold that will be used as a decision factor within the interval studied :

- geological formations bearing a natural GR activity characterized by :

$$GR_{Threshold} < GR < GR_{max}$$

are considered as Sandy Clay.

- geological formations with a natural GR activity characterized by :

$$GR_{min} < GR < GR_{Threshold}$$

are considered as a Clayey Sandstone.

The results for Sif Fatima 2 and Sif Fatima 3 boreholes are illustrated in fig.3 and fig.4 that shed light on the obtained segmentation. Moreover, the depth distribution of the different facies is given in table II and table III.

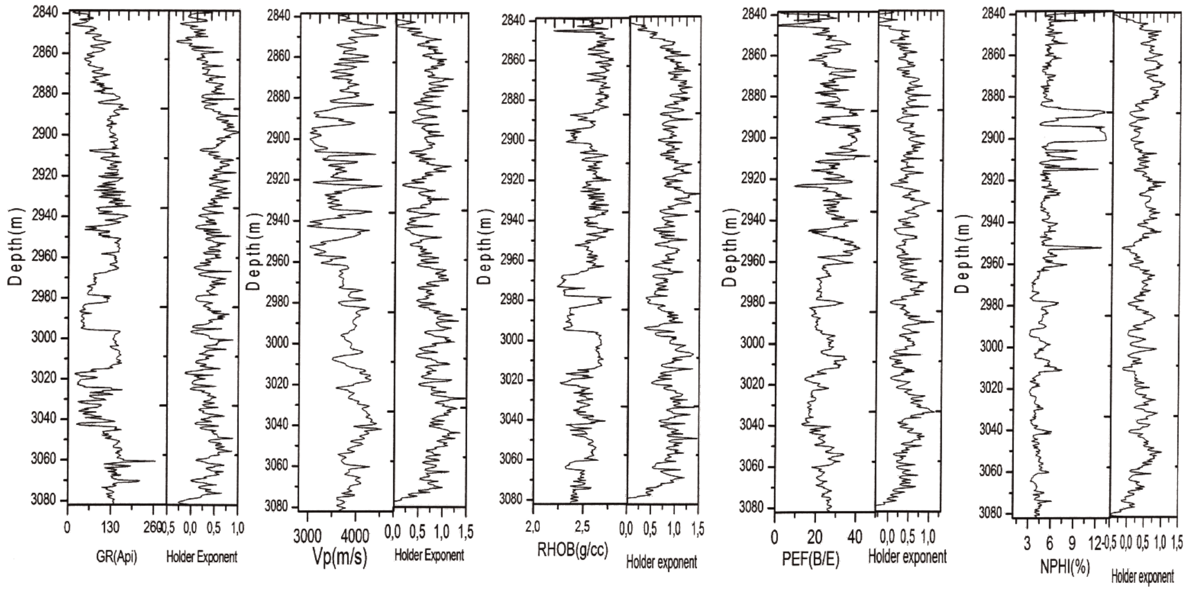

Fig. 3 - Measured well-logs data for Sif fatima2 borehole: GR, Vp, RHOB, PEF, NPHI and their corresponding Hölder exponents.

Traces des diagraphies du puits Sif Fatima 2 : GR, Vp, RHOB, PEF, NPHI et les exposants de Hölder correspondants.

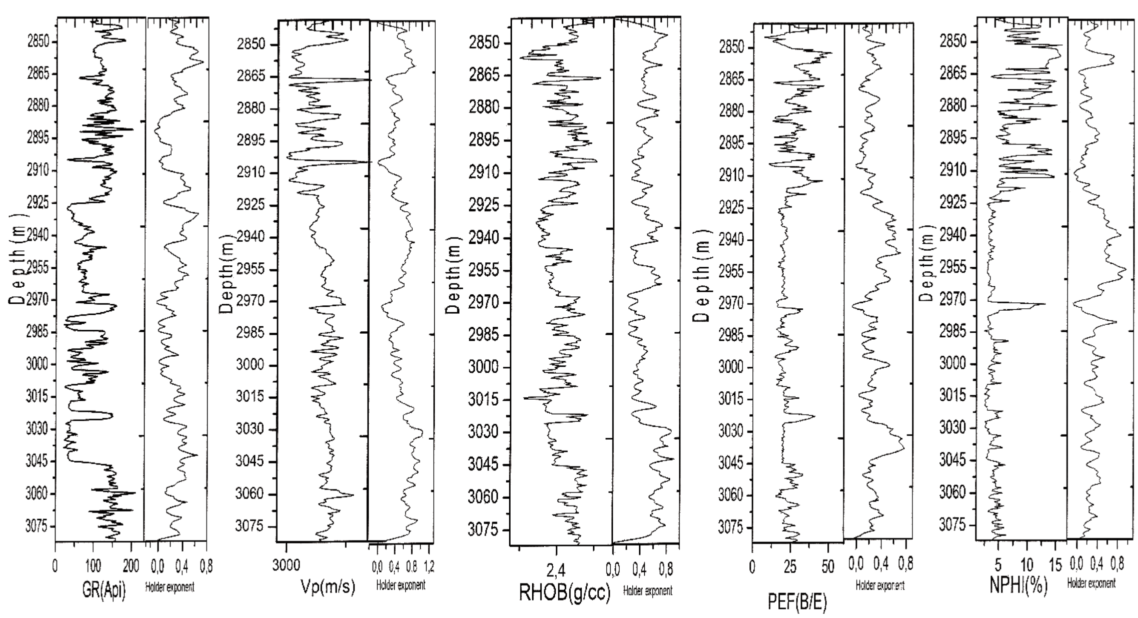

Fig. 4 - Measured well-logs data for Sif-Fatima 3 borehole: GR, Vp, RHOB, PEF, NPHI and their corresponding Hölder exponents.

Traces des diagraphies du puits Sif Fatima 3: GR, Vp, RHOB, PEF, NPHI et les exposants de Hölder correspondants

Table II - Lithofacies intervals derived from the GR signal for Sif-Fatima 2 well

Description en fonction de la profondeur des différents faciès du puits Sif Fatima 2 obtenus à partir du signal GR

Depth interval (m)	Petrographical description
2838.50 -2887.20	Clayey sandstone with increase of the percentage of clay with depth
2887.20- 2913.00	Clay, sometimes slightly sandy
2913.00-2950.50	Metric alternating of Clayey Sandstone and clay
2950.50-2969.00	Clay with the presence of a Clayey Sandstone layer
2969.00 -2997.50	Clayey sandstone becoming clean at the bottom with the intercalation of sandy clay
2997.50 -3017	Thick layer of clay sometimes slightly sandy
3017 -3062.50	Metric alternating of sandstone and clay
3062.50 -3082	Sandy clay

Table III - Lithofacies intervals derived from the GR signal for Sif-Fatima 3 well

Description en fonction de la profondeur des differents facies du puits Sif Fatima 3 obtenus à partir du signal GR

Depth interval (m)	Petrographical description
2838.50-2849.70	Metric alternating of sandstone and clay beds
2849.70 -2857.73	Level of clayey sandstone significantly homogeneous
2857.73 -2870.40	Sandy clay
2870.40 -2885.50	Clays, presence of some Clayey Sandstone traces
2885.50-2899.86	Metric alternating of sandstone and clay
2899.86-2927.13	Clay and sandy clay with intercala-tion of sandstone metric beds
2927.13-2973.40	Clayey sandstone with increase of the percentage of clay with depth
2973.40 -3027.50	Metric alternating levels of sands tone and clay
3027.50 -3047.50	Thick sandstone beds sometimes slightly clayey
3047.50 -3082	Clay with some clayey sandstone traces

5. RESULTS AND DISCUSSIONS

In the well log case, one may explore for depth regions scaling differently than others, and search for characterizing the complex set of not isolated singularities, provide their scaling behaviour persists over a wide enough scale range. In such cases the more appropriate tools are those referred as global multiscale analysis (see Zaourar and *al.*, 2006b).

5.1. Wavelet-based estimator analysis

Local variations in the power law exponents are estimated by using the CWT algorithm implemented (*in* Ouadfeul, 2006). The figures 3 and 4 illustrate for Sif Fatima 2 and Sif Fatima 3 respectively, the wavelet Hölder exponent profiles obtained independently from the considered logs, compared to their respective raw signals. All the Hölder profiles present irregular variations suggesting the complex transitory structures and the fractal characteristics of the signal. One can observe a good correspondence between the Hölder regularity profiles and lithology. This result is very impor- tant, because from each set of the analyzed regularity log we obtain similar segmentations that can be related to lithological units (Zaourar and *al.*, 2006a).

To further improve this approach, we show that the use of the estimated wavelet Hölder exponents rather than the raw data measurements allow to enhance a classification process initiated by Kohonen's self organizing map .

5.2. Input data scaling and model parameterization

We have established a model using the Sif Fatima 2 five logs (GR, RHOB, NPHI, PEF and Vp) of the learning Kohonen's map. After the self-organizing process, the map approximates the probability density distribution function of the training data. When the learning process is finished, each neuron will automatically recognize a combination of log responses. At this point, each vector of the data set could be sequentially processed in order to be assigned to the neurons they have excited: it's the classification stage. For numerical computation, we considered 1601 data points derived from preliminary interpretation of natural gamma ray of Sif Fatima 2 borehole as labels. In this study, we consider this preliminary interpretation as a pseudocore. For each depth, the pseudocore provides the lithological character of the rocks. This information is required to label each neuron of the map. Accordingly, the map becomes a classifier. Recall that the sampling rate for Sif Fatima2 borehole is 0.1524 m which provides a better resolution. For this reason; we use its well logs data as a learning base for training the map data. When the network is stable and represents almost the data space, we exploit the obtained map to classify Sif Fatima 3 borehole lithofacies using its well logs measurements.

The originality of our approach is to exploit the same algorithm using the corresponding set of Hölder exponents estimated for Sif Fatima 2 borehole data by CWT, to train a Kohonen's map. Figure 5 shows the lithofacies obtained for Sif Fatima 2 drilling using respectively the GR signal segmentation, the Kohonen's SOM output with raw data as input and finally the Kohonen's SOM output with the Hölder exponents as input. The similar results for Sif Fatima3 are illustrated in figure 6.

5. 3. Discussion of the classification results

We have outlined above that, the main TAGI objective reservoir contains only four lithological units which are: The clay, sandstone, clayey sandstone and Sandy Clay. The output of the neural machine should be one of these previous lithologies. Figure 5a and 5b show the obtained lithofacies using the Self Organizing Map with the raw data as an input (SOMr) compared to the pseudocore of the Sif Fatima 2 drilling. One can remark that the main transitions are detected; in addition the SOMr has given more geological details. As mentioned previously, our main task in this work is to enhance the classification results by the SOM

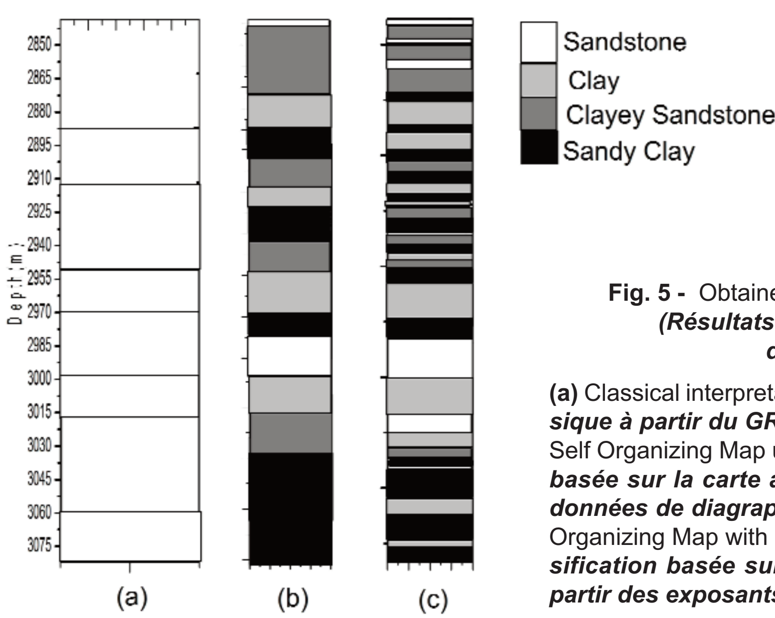

Fig. 5 - Obtained lithofacies for Sif Fatima 2 borehole ***(Résultats de classification du lithofaciès du puits Sif Fatima 2)*** :

(a) Classical interpretation based on the GR ***(Interprétation classique à partir du GR)***. **(b).** Classification based on the Kohonen Self Organizing Map using raw logs data as input ***(Classification basée sur la carte auto-organisée de Kohonen à partir des données de diagraphies)***. **(c).** Classification based on the Self Organizing Map with estimated Hölder exponents as input ***(Classification basée sur la carte auto-organisée de Kohonen à partir des exposants de Hölder)***.

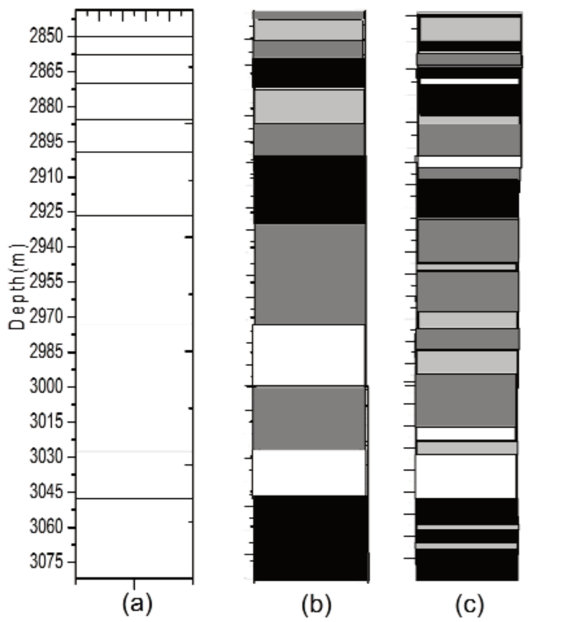

Fig. 6 - Obtained lithofacies for Sif Fatima 3 borehole ***(Résultats de classification du lithofaciès du puits Sif Fatima 3)*** :

(a) Classical interpretation based on the GR ***(Interprétation classique à partir du GR)***.
(b). Classification based on the Self Organizing Map using raw logs data as input ***(Classification basée sur la carte auto-organisée de Kohonen à partir des données de diagraphies)***.
(c) Classification based on the Self Organizing Map with estimated Hölder exponents as input ***(Classification basée sur la carte auto-organisée de Kohonen à partir des exposants de Hölder)***.

using the Hölder exponents (SOMh) rather than the raw data as input. Indeed, we observe (fig.5c) that each level is clearly identified; furthermore each layer presents additional subunits. For instance, if one consider the 2838.50-2887.20 m depth interval mainly composed of clayey sandstone according to the pseudocore as illustrated in figure 5a, it is rather easy to observe clayey sandstone the presence of eight subunits composed alternatively by sandstone, clayey sandstone and clay. For the second and third layers (fig.5a), the SOMh (fig.5c) detects more subunits marked by finest transitions of clay comparatively to SOMr (fig.5b). However, layers between 2970 and 3015 m (fig.5a) representing the clayey sandstone and clay were classified similarly for both techniques (fig. 5b and c).

In the other hand , the layer between 3017-3062.50 m composed by metric alternating of sandstone and clay (table.I) is the better described by SOMh (fig.5c) which specify two sandstone levels : one in the top and a thin one inserted in a sandy clay bed. However SOMr evaluates them as clayey sandstone and sandy clay respectively as showed in figure 5b.These observations comply with the pseudocore (table I and fig. 5a). The sandy clay level is clearly defined by SOMr, as illustrated in the last layer (fig. 5 b) located at 3060-3082 m depth interval. However, we can note that SOMh as illustrated in fig.5 c, exhibits clearly a thin clay intercalation in the interval 3065.64-3068 m, within the sandy clay. This observation is confirmed by the Gamma ray signal which shows a spike located at the same depth.

The SOM weights of connection obtained by the training of the SOMr and SOMh using respectively the Sif Fatima 2 borehole data and the corresponding Hölder exponent are used to deduce lithofacies for the Sif Fatima3 borehole. We summarized the obtained results in figure 6. As expected, the SOMh presents more transitions and details than SOMr. These remarks tend to prove that the neural machine is well trained. Our results suggest that the Self Organizing Map model with the estimated Holder exponents as an input improve lithofacies classification.

6. CONCLUSION

The aim of this study is to realize more consistent lithologic interpretations of logs optimising the use of the CWT combined with the Neural Network. A Kohonen's Self Organizing Map neural network machine is developed and successfully applied on the well log data of Sif Fatima 2 and Sif Fatima 3 boreholes located in

Berkine Basin in order to classify lithofacies. The SOM with the Hölder exponents as input data provides a more satisfactory classification result. It is important to outline, that the calibration of data sets with classification derived from the Gamma ray log is legitimate because the studied interval is a limited part of the TAGI. Our results suggest an enhanced facies characterisation which leads an accurate interpretation process to update the reservoir architecture.

By implementing our method, we have demonstrated that it is possible to provide an accurate geological interpretation within a short time in order to take immediate drilling and completion decisions but also, in a long term purpose, to update the reservoir model. Since of its computational efficiency, it is proposed that the present methods can be further exploited for analysing large number of borehole data in other areas of interest.

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