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Formation interface detection using Gamma Ray log: A novel approach

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Abstract

There are two methods for identifying formation interface in oil wells: core analysis, which is a precise approach but costly and time consuming, and well logs analysis, which petrophysists perform, which is subjective and not completely reliable. In this paper, a novel coupled method was proposed to detect the formation interfaces using GR logs. Second approximation level (a_2) of GR log gained from optimum mother wavelet decomposition was used for formation interface detection. Short time Fourier transform (STFT) of a_2 was gained since the window band was fixed in the entire of well depths. Inverse STFT of various windows of transformed data was gained, which creates various signals in depth domain. To this end, a novel formulation was developed to obtain modified signal for formation interface detection. The mean of various resulted signals creates a smooth signal the logarithm well of which highlights formation interfaces. Synthetic data were used to test the applicability of proposed algorithm. Accordingly, GR logs corresponding to five different wells located in an oilfield in south of Iran also were used to investigate the accuracy and applicability of the proposed method. Lastly, the validation process took place by comparing the results of core data analysis and the proposed method. Good agreements were obtained between these approaches, demonstrating the applicability of the proposed methodology.

Keywords: *Formation interface; Wavelet transform; Short time Fourier transform; GR log.*

1. Introduction

Formation interfaces detection is one of the principal tasks in reservoir rock boundary identification of oil wells. Generally, there are two customary methods for formation interface identification: core data analysis [7] and well logs interpretation [5, 7] both of which suffer from a few shortcomings. It should be mentioned that seismic data are useful tool for formation interface identification [1], but in comparison with the core and log data, their resolution is too low.

First attempts to detect formation interface using well logs was done in 1983 [9]. They applied Walsh transform on well logs and proposed a methodology which discriminated formation interfaces. Of course, their method was unable to detect the interface of thin layered interfaces. Later, an automated method was developed to detect lithology boundaries using Walsh transform, which increased the resolution of interface detection [10]. Few researchers have tried to utilize wavelet instead of Walsh transform, because of its localization properties. For example, wavelet transform was applied to SP and GR logs, and coefficients were used for stratigraphic formation interface identification [13]. They also developed a combined wavelet-Fourier transform method, which was sensitive to location and size of frequency bands. They introduced unique frequency bands for formation boundaries detection based on wavelet transform of SP and GR logs. Moreover, other approaches were also proposed for formation boundaries detection. Among them, Hsieh *et al* (2008) developed a fuzzy logic algorithm, which applied to aquifer well logs for lithology identification.

The most commonly used log in interface detection algorithms is GR. As it has been confirmed, GR is a well known log which is highly affected by lithology variations and almost is available in majority of oil wells. Therefore, the methodology which uses GR log for formation interface detection is a wide spread technique.

In this paper, a novel combined approach is presented which employs only GR log for identification of formation boundaries. The proposed approach is an extension to the algorithms introduced by Miati and Tiawari (2005) and Pan *et al* (2008). They have considered GR as a signal which represents the specific energy corresponding to any formation. Signal processing techniques, e.g. signal transformation and filtering were the approaches they used for formation interface detection. In this work, wavelet and Fourier transform (FT) were used to solve the mentioned issue. The applicability of the proposed methodology was investigated using the analysis of synthetic data and GR logs of five wells in an oilfield located in south of Iran.

2. Methodology

In the present study, four different techniques were used for signal processing of GR log and formation interface detection. They are explained briefly in the following sections.

2.1. Short time Fourier transform

GR well logs can be processed as discrete signals and transformed into another domain, depending upon the kernels used [14]. Perhaps the most well known signal processing method is FT, which breaks down a signal into constituent sinusoids of different frequencies [12]. For stationary signals, it is an optimal method to analyze the frequency content [8], while for non-stationary signals, a transformation method with time resolution capability is needed. STFT is a Fourier-related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over location [13].

The discrete STFT $STFT\{x(t)\}$ of a non-periodic signal $x(n)$ is defined by Eq. 1 [8]:

$$STFT\{x(n)\} \equiv X(m,\omega) = \sum_{n=-\infty}^{\infty} x(n)\,\omega(n-m)\,e^{-j\omega n} \quad (1)$$

where $e^{-j\omega n}$ is Fourier orthogonal function, and $\omega(n-m)$ is window function. The STFT is adapted to signals from real applications, which always have finite length.

2.2. Wavelet transforms

Wavelet transform was developed with the localization idea from Gabor’s Short-Time Fourier analysis and has been expanded further. Wavelets provide the ability to perform local analysis [4].

The following equation defines a discrete wavelet transformer (DWT) of a signal *x*(z) [3, 11, 6]:

$$DWT(\tau,s) = \frac{1}{\sqrt{s}} \int x(z)\,\overline{\psi}\left(\frac{z-\tau}{s}\right) dz \quad (2)$$

This function transforms signal *x*(z) using mother wavelet $\overline{\psi}(z)$ from the depth domain (z) to scale (s) domain with translation (τ). In equation (2), $z-\tau$ is the depth translation. The term $(\sqrt{|s|})^{-1}$ is a normalization factor for removingthe scale effect from wavelets with different scales.

In wavelet analysis, a signal decomposes to approximations and details coefficients; approximations are the high-scale, low-frequency components of the signal and details are the low-scale, high-frequency components [12]. Figure 1 shows the procedure of wavelet decomposition.

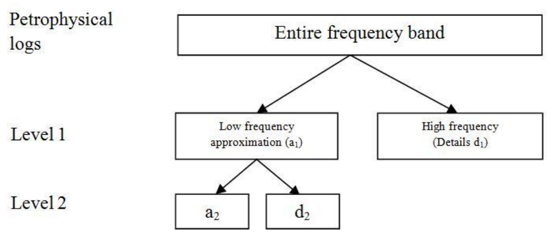

Figure1. Schematic well logs wavelet decomposition stages [15].

2.3. Optimum mother wavelet selection

There are various methods for optimum mother wavelet selection. In this study, an energy matching strategy has been used to choose optimum mother wavelets in order to analyze GR log data. In this strategy, GR log is first transformed from the depth–wavelength domain to frequency–wavelength domain using a FT to detect the dominant frequency bands. GR energy, which is equal to the sum of squared amplitudes in dominant frequency bands, is calculated in the identified dominant frequency bands. Then, GR is analyzed using different mother wavelets, and its energy in the identified dominant frequency bands is calculated. The optimum mother wavelet is the one whose match between signal energy in dominant frequency bands and the signal energy obtained from FT (in similar frequency bands) becomes maximum [2].

2.4. Developed algorithm

The following process defines the developed algorithm for formation interface detection in this study:

a. Decompose GR log by optimum discrete mother wavelet in order to obtain Second approximation level (a_2). a_2 is selected based on a trial and error algorithm.
b. Apply inverse wavelet transform to reconstruct a set of data from a_2. In this stage, a denoised-smooth GR log will be constructed its depth resolution of which is the same as raw data.
c. Take STFT of reconstructed data, in order to translateit to time-frequency domain in various windows.
d. Choose certain frequency band of spectrum of the reconstructed data, and consider it as a new data set.
e. Shift the frequency band and reply section d in the whole spectrum by equation 3:

$$12 . f < Y < 12 . (f+q) \quad , x=0,1 ,2, . . . ,(F/12-q) \qquad (3)$$

where f is the unit of frequency, F is the maximum GR frequency and q is an indicator of frequency band (window length as $q \in [2,4]$). Result of equation 3 will be smoother for narrower window lengths; otherwise the resulted signal will be much noisy. It should be mentioned that equation 3 is experimentally developed based on GR logs of five studied wells.

f. Take the inverse STFT of each new data set, and translate them to time domain, and obtain modified reconstructed data.
g. Take the average of absolute values of all modified reconstructed data to obtain average data.
h. Take logarithm of average data which is the last modified data.

The algorithm is abstracted as a flowchart (Figure 2).

3. Data

In current study, the proposed methodology is applied to analyze the synthetic and real data; these are briefly explained under the following rubrics.

3.1. Synthetic data

Synthetic data are generated with the following simple constraints:

a. Generate 10,000 data in the depth between 2300 and 3300 meters. Depth resolution is 10 cm and values of all data are equal to 10.
b. Deduct 6 units from data in interval 2790 and 3090 meters. This interval represents a clean carbonate formation. Other intervals represent shale formations.
c. Generate and add white noises. In all the synthetic data, mean and variance of white noise are equal to zero and 0.25 respectively (see Figure 3).

Generate another similar synthetic log, in which a thin interval of shale with high GR (as triangle) is visible (Figure 4).

3.2. Real data

The proposed methodology was applied on GR log of five wells (Figure 5) in an oilfield located in south of Iran. Core analysis and geological interpretation indicate the existence of eight formations in the studied depths of selected wells.

4. Results

The results of the methodology applied to synthetic and real data are presented in the following secions.

4.1. Synthetic data

Semi smooth synthetic GR logs are shown in figures 6.a and 7.a. The interface detection method was applied on synthetic data and results are shown in figures 6.b and 7.b. As it can be seen in figure 6.b, in binary log, two resulted picks are fitted on two synthetic formation boundaries. The important point is that the shapes of the picks are similar to sink function. On the other hand, amplitudes of the carbonate formation in boundaries are maxima, while it is minima in the center of the formation. For Second log, as it can be seen in figure 7.b, a shortcoming is visible. The result shows just one major pick the fitness of which is acceptable with the middle of thin synthetic shale formation; while we expect the algorithm detects formation's boundaries. It should be mentioned that here, q (window length) is selected equal to two.

4.2 Real data

As mentioned previously, eight formations which affect the GR, are located within the studied wells. Therefore, the studied depths are heterogeneous.

In the first step, studied depths were divided into semi homogenous depths from the aspect of GR behavior in frequency domain and geological experience. Optimum mother wavelet in each homogenous section of the wells is selected separately (Table 1).
FT was applied to GR log. Different frequency bands are considered to calculate the signal energy. The results are summarized in Table 2. In general, the signal frequency varies between 0 and 5000 Hz in all wells. From table 2 it can be concluded that more than 98% of the information is hidden in low frequency bands (right column in Table 2). For example, in well 2, more than 99% of GR energy is hidden in the frequency band 1–240 Hz (i.e. within less 5% of frequency range). Also in this well about 96% of signal energy is concentrated near zero frequency. Thus, it is not recommended that we search the GR information in high frequency bands. In this study, a_2 of GR logs, which are determined based on final results, is used for formation interface detection.

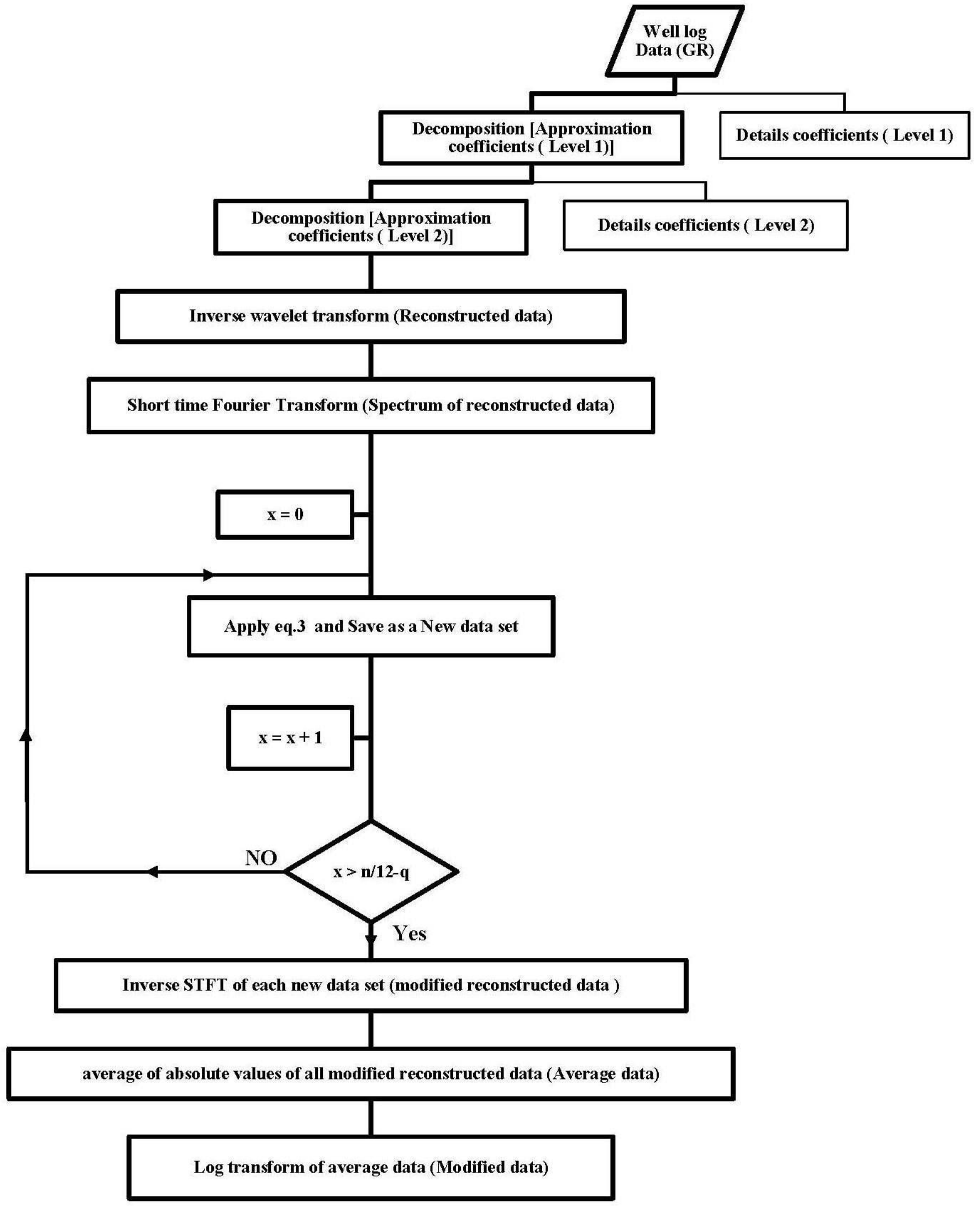

Figure 2. Flowchart of proposed methodology for formation interface detection.

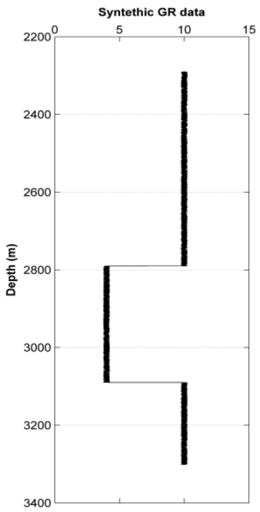

Figure 3. Synthetic generated GR data No#1.

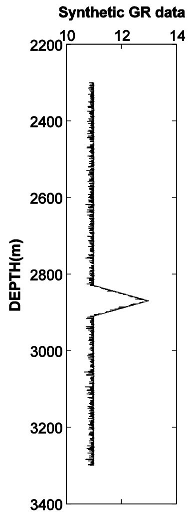

Figure 4. Synthetic generated GR data No#2.

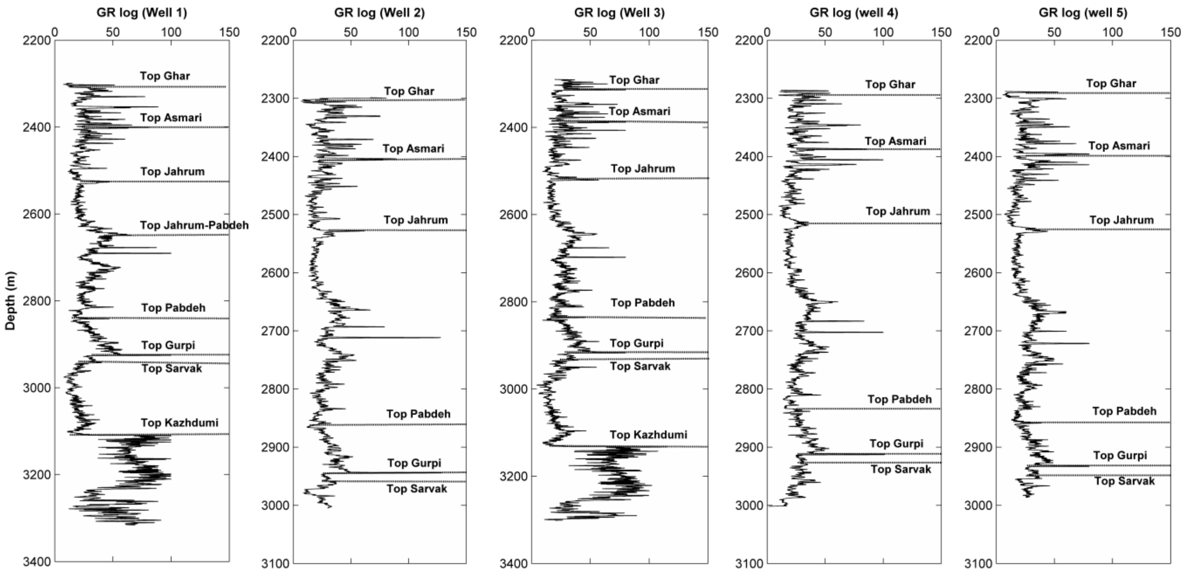

Figure 5. GR logs and top of the formations in five studied wells.

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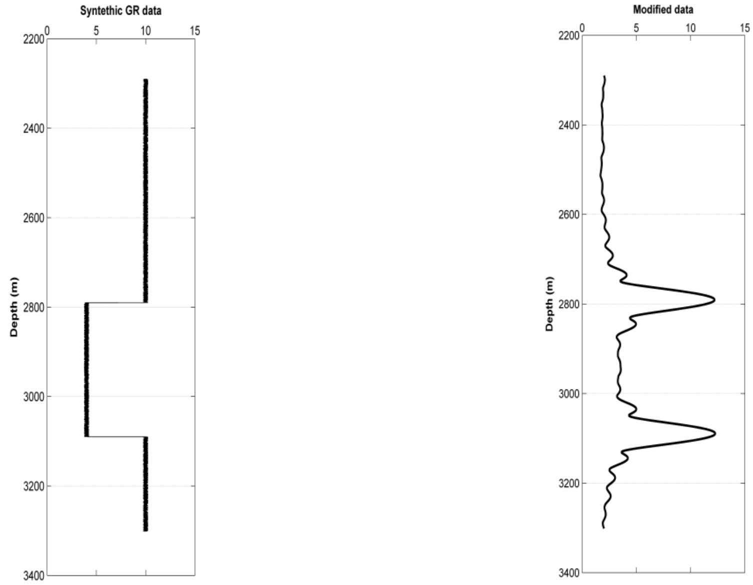
Table 1. Confine the zones distinct to identification optimum mother wavelets in five studied wells.

Formation	Well 1	Well 2	Well 3	Well4	Well5
Section one (cap rock)	----	bior3.5	bior5.5	Bior3.3	Bior3.7
Section two (Ghar -upper Asmari)	bior3.7	bior6.8	rbio6.8	rbio3.1	rbio3.9
Section three(lower Asmari - Sarvak)	coif3	dmey	dmey	bior5.5	dmey
Section four (Kazhdomi)	rbio3.9	bior3.5	----	----	----

Table 2. Signal energy percentage of GR log at low frequencies in five studied wells.

Frequency band	1- 30	31-60	61-90	91-120	121-150	151-180	181-210	211-240	1 -240
Well 1	96.7	0.68	0.48	0.23	0.26	0.20	0.17	0.20	98.94
Well 2	96.08	0.88	0.59	0.39	0.43	0.28	0.23	0.21	99.11
Well 3	96.9	0.69	0.21	0.33	0.21	0.19	0.14	0.12	98.85
Well 4	96.40	0.61	0.72	0.43	0.34	0.31	0.24	0.21	99.27
Well 5	96.81	0.76	0.49	0.32	0.30	0.29	0.17	0.13	99.29



(a) **(b)**

Figure 6. a) Synthetic GR data No.#1 b) The result of applying the methodology on synthetic data, which shows boundaries clearly.

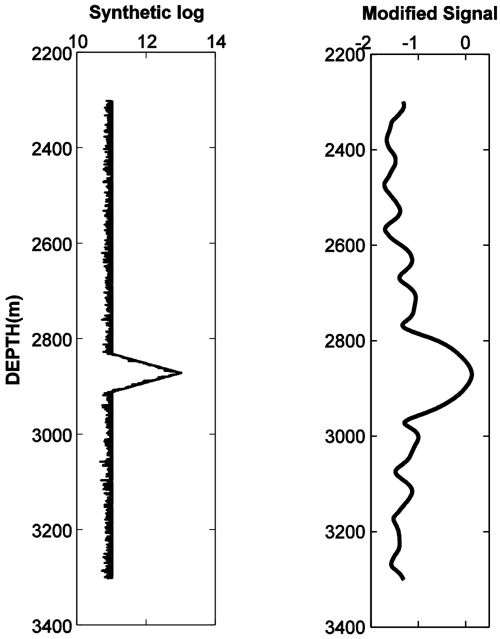


Figure 7. a) Synthetic GR data No.#2 b) The result of applying the methodology on synthetic data.

Following process over data is:

a. Reconstructed GR signals are resulted from inverse wavelet transform of a_2 (figure 8).
b. Spectrum of reconstructed signal is resulted from FT of reconstructed GR (figure 9).
c. The window lengths chosen for studied wells are reported in table 3.
d. Equation 3 is applied on spectrum to obtain the new series of data.
e. Inverse FT is applied to all achieved new data.
f. Modified signal is calculated by taking the logarithm of average absolute values in all modified reconstructed data, which is the final result.

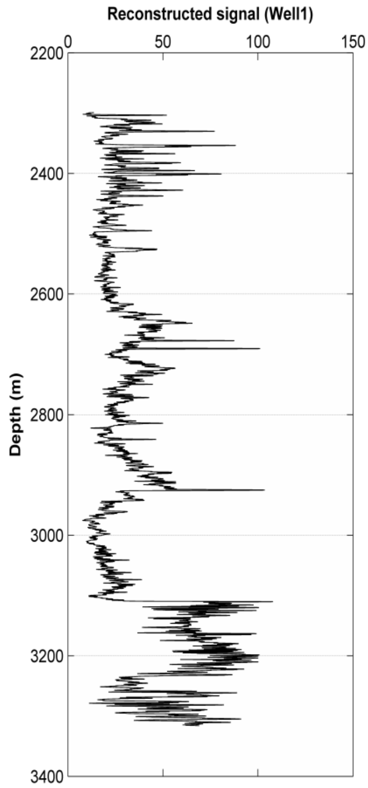


Figure 8. Reconstructed signal yield from inverse a2 of GR log of well 1.

Final results (Figures 10.a to 10.e) almost reveal the formation interfaces. Numerical results are listed in Table 4. As shown in Figure 10 and Table 4, the proposed methodology has a few shortcomings. For instance, it could not detect the top of the Sarvak formation which is probably due to the thinness of this formation. Of course, achieving the high resolution result is possible by increasing the window size.

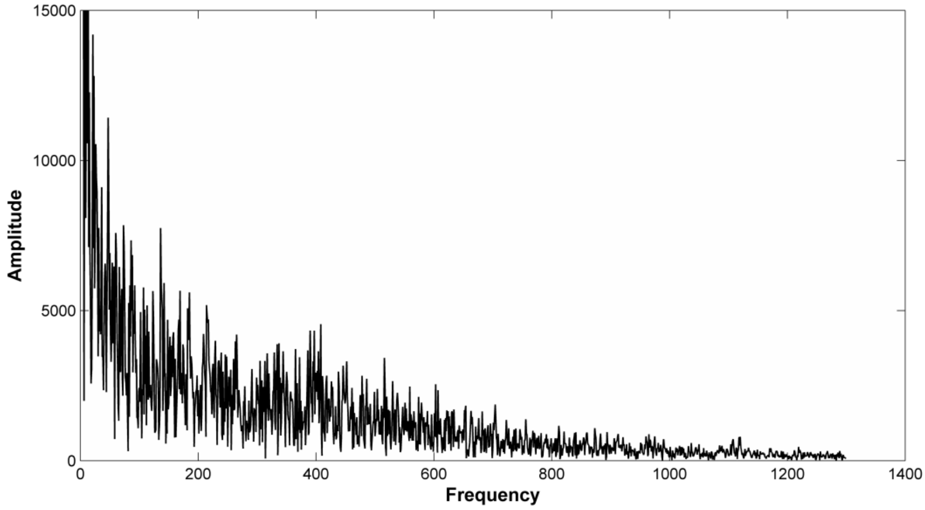
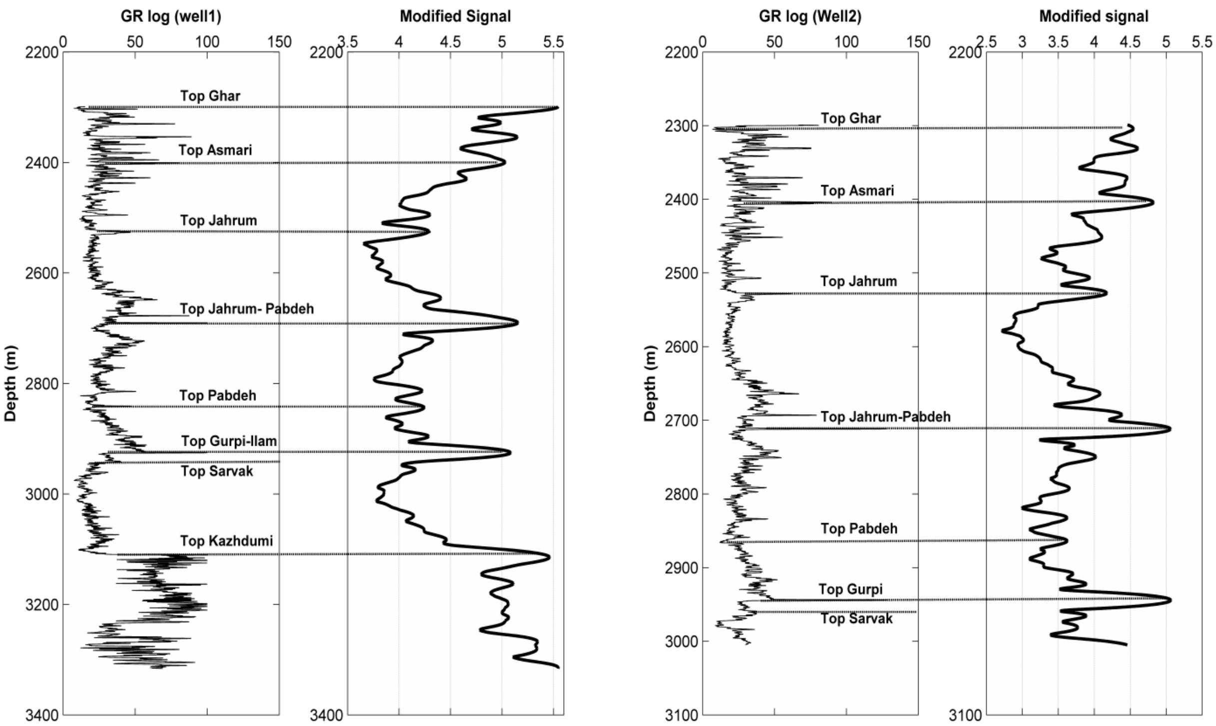


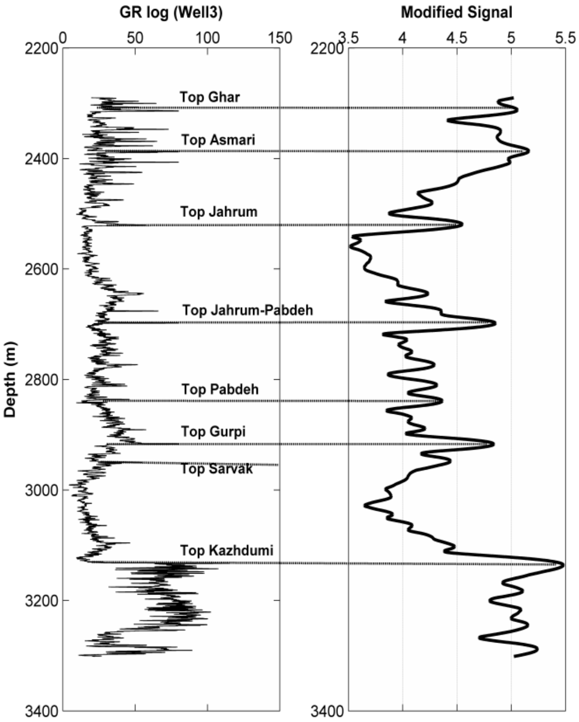
Figure 9. FT of reconstructed signal (figure 8).

Table 3. Window length was obtained for five studied wells.

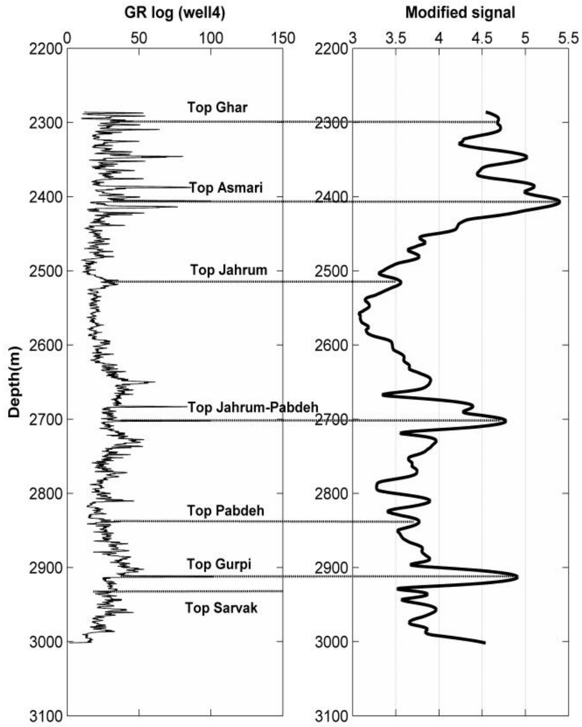
	Well1	Well2	Well3	Well4	Well5
Window length	4	2.5	4	3.5	2.6



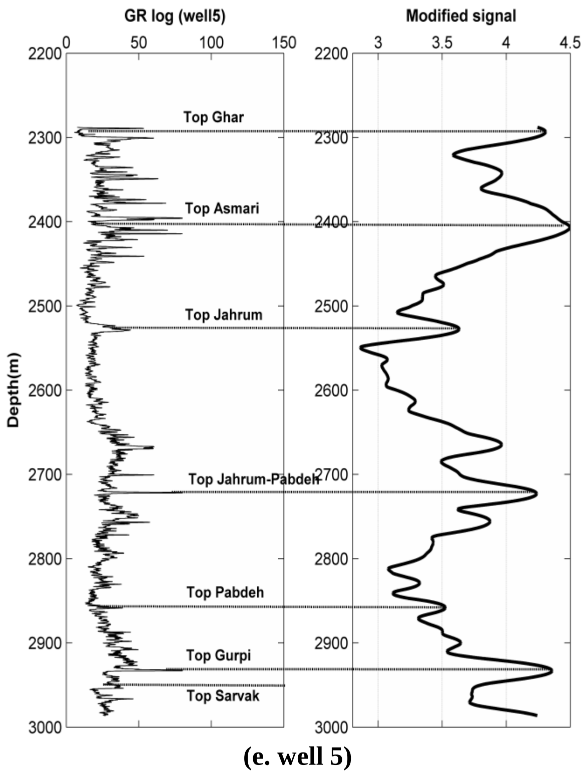
(a. well 1) **(b. well 2)**



(c. well 3)



(d. well 4)



(e. well 5)

Figure 10. Modified signal of GR log and comparison between results and top of formation boundaries in a) well 1, b) well 2, c) well 3, d) well 4 and e) well 5.

Table 4. Numerical results and errors of formation interval detection algorithm for five studied wells.

Top formations	Depth (m)	Well 1	Well 2	Well 3	Well 4	Well 5
Top Ghar	core	2309	2309	2290	2296	2298
	proposed algorithm	2303	2305	2305	2299	2295
	error	6	4	15	3	3
Top Asmari	core	2406	2403	2389	2390	2395
	proposed algorithm	2401	2406	2384	2400	2400
	error	5	3	5	10	5
Top Jahrum	core	2524	2530	2516	2514	2522
	proposed algorithm	2524	2526	2515	2512	2525
	error	0	4	1	2	3
Top Jahrum-Pabdeh	core	2645	-------	--------	--------	--------
	proposed algorithm	2685	2712	2695	2700	2723
	error	40	0	0	0	0
Top pabdeh	core	2848	2866	2841	2840	2861
	proposed algorithm	2846	2865	2841	2840	2860
	error	2	1	0	0	1
Top Gurpi	core	2924	2943	2916	2912	2932
	proposed algorithm	2924	2943	2916	2912	2932
	error	0	0	0	0	0
Top sarvak	core	2943	2965	2934.7	2931.9	2954
	proposed algorithm	Not found	Not found	Not found	Not found	Not found
	error					
Top Kazhdomi	core	3110	--------	3133	---------	--------
	proposed algorithm	3113	--------	3133	---------	--------
	error	3	--------	0	---------	--------

In this study, various approximation levels were checked and it was observed that the final results are almost similar. Of course, with increasing the level, amplitude of the boundaries will decrease, whereas the shapes of modified signals are almost fixed. Meanwhile, window length (q in equation 3) is important in the proposed approach. By increasing the q, noise in modified signals increases, while the amplitude of boundaries remains unchanged. As a result, changing the decomposition level and window length partially affects the results.

5. Conclusion

In this paper, a new approach based on combined WT and STFT was proposed to analyze GR log data to identify formation interfaces. Core data and well logs interpretations were used to investigate the validation of the results. A comparison between the results and core analysis showed that the proposed methodology identifies formations interfaces precisely.

The results also showed a shortcoming of the proposed methodology when the thickness of the formations is too small. If the thickness of the formation is less than spatial resolution, the modified signal cannot distinguish the formation interface. Later developments on this method will be considered to get rid of this shortcoming.

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