DENOISING OF PERMANENT DOWNHOLE PRESSURE DATA USING THE DISCRETE WAVELET TRANSFORM

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Abstract. *Permanent Downhole Gauges (PDG) for pressure and temperature are very common in oil and gas wells. The data collected by the PDG are used for monitoring the well condition and reservoir performance and, additionally, may provide new and complementary information for reservoir characterization. PDG record data at high sampling rates. The computational analysis of this large volume of data requires a previous processing for the removal of outliers and noise and for the reduction of the filtered data to a representative and tractable size. The Discrete Wavelet Transform (DWT) and the Multiresolution analysis were used successfully for this purpose. The denoising process was accomplished by the wavelet shrinkage method. This method consists in the decomposition of a signal in approximation and detail coefficients through low pass and high pass filters, respectively. The coefficients are modified, according to a thresholding rule, to remove the noise before the reconstruction of the original signal. The final result depends on the kind of wavelet and resolution level used for the decomposition process, the method used to estimate the noise level present on the signal, and the rules used to modify the coefficients. In this paper, the performance of different wavelet type decomposition, noise threshold estimators and thresholding rules was investigated. Several combinations were tested on synthetic and actual data to establish a procedure that efficiently removes the noise and preserves the sharp features, characteristic of changes in production or injection rates. In some cases, high oscillations appeared near the signal discontinuities, particularly for the soft thresholding rule with the universal threshold. The best results on suppressing the Gibbs-like artifacts were achieved by the combination of the Daubechies wavelet with the Firm shrinkage rule and Minimax threshold. The selected method was proved effective when applied to the denoising of actual PDG data.*

Keywords*: Well Test Analysis, Permanent Downhole Pressure Gauge, Reservoir Characterization.*

1. INTRODUCTION

Wellbore pressure is a very important source of data used in reservoir engineering to monitor reservoir conditions, to select recovery schemes, and to forecast its performance. The changes in the reservoir pressure are characteristic of reservoir properties themselves. Therefore, the reservoir properties can be inferred through comparison between the pressure response and a model, which can be used for future reservoir management. Transient tests are performed in order to observe the pressure response corresponding to flow rate changes during a time period.

Wells are equipped with PDG's in order to monitor well behavior in real time. This continuous pressure measurement makes it possible to observe reservoir changes and to make operational adjusts, to avoid accidents and improve the recovery.

Although the permanent downhole pressure gauges (PDG) installation was started in the 90's, there are older publications, which discuss PDG applications and benefits. The topics discussed were its application to optimize the production, localize operational problems, reservoir monitoring, its use in different well types and recovery processes, information extraction for well control, its installation and reliability.

The PDG data sets are very large, it may contain millions of measurements, and it may provide more reservoir information than the traditional transient pressure tests. A long-term data analysis reduces uncertainty in the interpretation. Furthermore, this kind of data may show how the reservoir properties change while fluid is produced. However, using this large amount of data is not trivial. In order to make possible a reliable interpretation it is necessary to pre-process the data. This pre-processing, composed by seven steps, was suggested by Athichanagorn et al. (2002).

This paper discusses just one of these steps: the PDG data denoising. The discrete wavelet transform is a tool used successfully to remove noise from these kinds of data. The wavelet analysis applied to PDG data was reported by many authors including Kikani and He (1998), Athichanagorn et al. (2002), Ouyang and Kikani (2002) and Ribeiro et al. (2006). In Antoniadis et al. (2001), there is a discussion about wavelet transform use in nonparametric regression and a review about wavelet literature related to data filtering.

Based in these previous studies, this work compares the performance of different combinations of wavelet families, thresholds and shrinkage rules, at different decomposition levels, for the denoising of PDG data. For this study, synthetic data from numerical reservoir modeling and actual PDG data were used.

The results were classified as best, intermediate and worst according to its performances. The combinations of the firm shrinkage rule with the minimax threshold and the hard shrinkage with the minimax and universal thresholds showed the best results. In general, the Daubechies 4 wavelet at the last decomposition level presents the best performance of all combinations tested. The Biorthogonal wavelet showed heterogeneous behavior and the worst results.

2. MATHEMATICAL BACKGROUND ON WAVELET TRANSFORM

The wavelet transform has a wide range of application in signal investigation from different physical phenomena. The most attractive features of wavelet transform to analyze signals are its ability to separate high frequency contents from low frequency components and to identify and locate signal discontinuities. In the petroleum engineering literature, this analysis has been applied in many different problems. One of these problems is the denoising of pressure data from permanent downhole gauges, to estimate reservoir characteristics.

The basic form of the wavelet ($\psi(t)$) is called the *mother* wavelet or *analyzing* wavelet. The wavelet families are building by manipulation of basic functions, which makes it more flexible. The first step stretches and squeezes the wavelet (dilation, represented by parameter a) and the other moves it along the time axis (translation, represented by parameter b). So, the wavelet transform of a signal, $f(t)$, at scale a and location b is defined as:

$$Wf(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\psi\left(\frac{t-b}{a}\right) dt, \qquad (a \neq 0) \tag{1}$$

The wavelet analysis is associated with a scaling function ($\phi(t)$). This function is a wavelet complementary transform, represented by:

$$Cf(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\phi\left(\frac{t-b}{a}\right) dt, \qquad (a \neq 0) \tag{2}$$

Equations (1) and (2) are used to decompose the signal in detailed components, using the wavelet transform (Eq. (1)) and approximation components, using the scaling transform (Eq. (2)). So, the signal can be represented by combining detail and approximation contents. This process can be repeated several times, using the scaling coefficients at one level as input to the next, so the signal is decomposed in many levels. Analyzing different levels, different signal features can be studied. This decomposition is called the pyramidal algorithm.

There are a large number of wavelet functions for several applications. Choosing one for a particular study depends on the nature of the signal and what physical phenomena or process is analyzed. In this paper, Daubechies, Symmlet, Coiflet and Biorthogonal wavelets were used.

Daubechies family is the most used in petroleum engineering applications. The functions are orthogonal with compact support, they present a finite number of complementary transform components:

$$\varphi(x) = \lim_{l \to \infty} \eta_l(x) \tag{3}$$

and η_l is determined by

$$\eta_l = \sqrt{2} \sum_n \alpha(n) \eta_{l-1}(2x-n) \ , \tag{4}$$

where α_i are coefficients of the filter. The transform with N void moments is obtained by:

$$\psi(t) = \sum (-1)^n \alpha_N(-n+1)\varphi_N(2x-n) \ . \tag{5}$$

For example, for $N = 1$ the simplest wavelet, called the Haar wavelet (discontinuous and looks like a step function), is obtained:

$$\psi(t) = \begin{cases} 1, & 0 \le t \le 1/2 \\ -1, & 1/2 \le t \le 1 \\ 0, & 1 \le t \end{cases} \ . \tag{6}$$

Symmlet and Coiflet families, developed by Daubechies (Addison, 2002), are functions with compact support. The wavelet will be perfectly symmetric and anti-symmetric when the Biorthogonal wavelet families are used (Addison, 2002).

In this work the Daubechies wavelets of orders 1, 2, 4, 6 and 8 were used. Additionally, Symmlet and Coiflet wavelet families with orders 2, 4, 6, 8 and 1, 2, 3, 4, 5, respectively, and the biorthogonal spline wavelets 13, 22, 26, 33, 35 were also applied for comparison purposes.

3. DENOISING BY WAVELET THRESHOLDING

Denoising is a procedure used in a specific data set to reduce the dispersion and fluctuation of its values in order to extract its more representative features. One of the best methods to denoise signals is the wavelet thresholding method. While most of denoising methods tend to smoothing the sharp data features, the wavelet thresholding method, generally, preserve most of them.

To remove the noise of PDG data, the signal is decomposed using a wavelet procedure that follows the pyramidal algorithm, where the signal is divided into approximation and detail at each decomposition level, (Athichanagorn, 2002). After decomposition, the detail signal could be denoised by some thresholding method. Donoho and Johnstone (1994) introduced the hard and soft shrinkage rules for this application. When using the hard shrinkage rule the detail signals below a specific threshold (λ) are set to zero and the denoised signal is reconstructed using the smoothed data:

$$\delta_\lambda^H = \begin{cases} 0, & |d_{j,k}| \le \lambda \\ d_{j,k}, & |d_{j,k}| > \lambda \end{cases} \quad . \tag{7}$$

The soft shrinkage rule, besides setting to zero the signal less than λ, reduces λ from the signal value out of this band:

$$\delta_\lambda^S = \begin{cases} 0, & |d_{j,k}| \le \lambda \\ d_{j,k} - \lambda, & d_{j,k} > \lambda \\ d_{j,k} + \lambda, & |d_{j,k}| < -\lambda \end{cases} \quad . \tag{8}$$

Athichanagorn (2002) observed that the hard shrinkage rule is better than the soft on zones close to data discontinuities. However, the hard rule is not able to suppress some noise signals on continuous data zones, while soft rule is able to. An alternative technique used by Gao and Bruce (1997) to overcome the hard and soft shrinkage limitations was the firm shrinkage rule

$$\delta_{\lambda_1,\lambda_2}^F = \begin{cases} 0, & |d_{j,k}| \le \lambda_1 \\ sgn(d_{j,k}) \frac{\lambda_2(|d_{j,k}| - \lambda_1)}{\lambda_2 - \lambda_1}, & \lambda_1 < |d_{j,k}| \le \lambda_2 \\ d_{j,k}, & |d_{j,k}| > \lambda_2 \end{cases} \quad . \tag{9}$$

Note that this method uses the hard and soft thresholding principles, providing better results when compared to them. However, it is necessary to specify two threshold values, which is a computational disadvantage. Therefore, Gao (1998) considered the garrote shrinkage rule

$$\delta_\lambda^G = \begin{cases} 0, & |d_{j,k}| \le \lambda \\ d_{j,k} - \lambda^2 / d_{j,k}, & |d_{j,k}| > \lambda \end{cases} \quad . \tag{10}$$

Tests with the garrote rule showed that it is better than hard and soft rules and as good as firm, and only one threshold value is necessary. In the same way, Antoniadis and Fan (2001) considered the SCAD rule, expressed by

$$\delta_\lambda^{SC} = \begin{cases} sgn(d_{j,k}) * \max(0, |d_{j,k}| - \lambda), & |d_{j,k}| \le 2\lambda \\ \frac{(\alpha-1)d_{j,k} - \alpha\lambda\, sgn(d_{j,k})}{\lambda - 2}, & 2\lambda < |d_{j,k}| \le \alpha\lambda \\ d_{j,k}, & |d_{j,k}| > \alpha\lambda \end{cases} \quad . \tag{11}$$

The threshold values used in the thresholding methods may be specified by several methodologies. The most applied is the universal threshold,

$$\lambda^U = \sigma\sqrt{2\log(n)} \quad , \tag{12}$$

where n is the number of points and σ the standard deviation of the signal noise. The universal threshold removes most of the signal noise, however, its utilization may over smooth sharp features of the signal, (Olsen and Nordtvedt, 2005).

The minimax threshold follows the same universal principle and may be understood as its adjust. The minimax threshold values are smaller than the universal threshold, but both of them tend to assume high values. The minimax threshold has been derived by Donoho and Johnstone (1994) for soft shrinkage, by Bruce and Gao (1996) for hard shrinkage, by Gao and Bruce (1997) for firm shrinkage, by Gao (1998) for garrote shrinkage and by Fan and Li (1999) for SCAD. In this study the minimax threshold values were calculated by logarithmic interpolation of tabulated values published on the references cited.

Trying to obtain an optimum threshold value, Donoho and Johnstone (1994) introduced the SURE scheme, that uses wavelet coefficients at each resolution level j to choose a threshold value λ_j. The idea is to use Stein's unbiased risk criterion (see Stein, 1981).

In this paper the results obtained from several combinations among shrinkage rules and threshold values, wavelet families, and decomposition levels are presented. The main objective of the comparison is to find the best technique for denoising PDG data, preserving the sharp features distinctive of production rate changes.

4. RESULTS

Several tests were performed to investigate the denoising methods performance. Three different flow models were used in the study: Radial Homogeneous Infinite Acting, Radial Homogeneous Closed Square with Partial Penetration and Injection Well in a Two Faults System (channel reservoir). The reservoir and fluid properties adopted may be found in Table 1. The data points were equally spaced in time with time step equal to 0.01 h. Figure 1 shows the pressure behavior for each flow model. Synthetic noisy data were generated adding random noise with zero mean to the original data set at three different levels (0.02, 0.04 and 0.06 x 10kPa).

Different combinations of shrinkage rules, thresholds and resolution levels were investigated. Table 2 shows a summary with the combinations tested. The wavelet decomposition procedure with smooth padding at the edges was applied in data sets of 2048, 16384 and 65536 points. Tests with these three different data sets proved that its size does not influence considerably the final result. The resolution level was chosen according to the maximum value between the formulas proposed by Olsen and Nordtvedt (2005) and Donoho and Johnstone (1994).

Table 1: Reservoir and fluid properties

Property	Value
Original Pressure *(x10kPa)*	250
Reservoir Temperature (^oC)	80
Permeability (*mD*)	500
Net Pay (*m*)	50
Porosity	0.25
Oil Formation Volume Factor ($m^3/std\ m^3$)	1.025
Oil Viscosity (*cp*)	5
Well Radius (*m*)	0.108
Total Compressibility (*1/10kPa*)	1.4×10^{-4}

Table 2: Shrinkage rules and thresholds

	Universal	SURE	Minimax
Soft	X	X	X
Hard	X	X	X
Firm			X
Garrote	X		X
SCAD	X		X

As the models employed are large the tests were performed on signal sections. A moving window through the time axis was used, starting on the first time value and testing sub-sets. The size of the window was fixed on the tests to maintain a standard comparison between the results.

To determine the best combination for each case, three comparison criteria were employed: the maximum value of the difference between the denoised and original signal (error), the standard deviation of the error and a visual verification of the denoised signal. The last criterion gives information about the Gibbs effect: signal oscillations, which occurs at discontinuities' neighborhood.

Observing the resolution level, we can verify that when it increases the difference between the original signal and denoised signal decreases in the continuous regions, with small improvements for high levels resolution. However, the Gibbs effect exceeds the original noise level, particularly when the soft shrinkage and the biorthogonal wavelets are used. This can be verified on Fig. 2, where the denoised signal shows high levels of oscillations near the signal discontinuity.

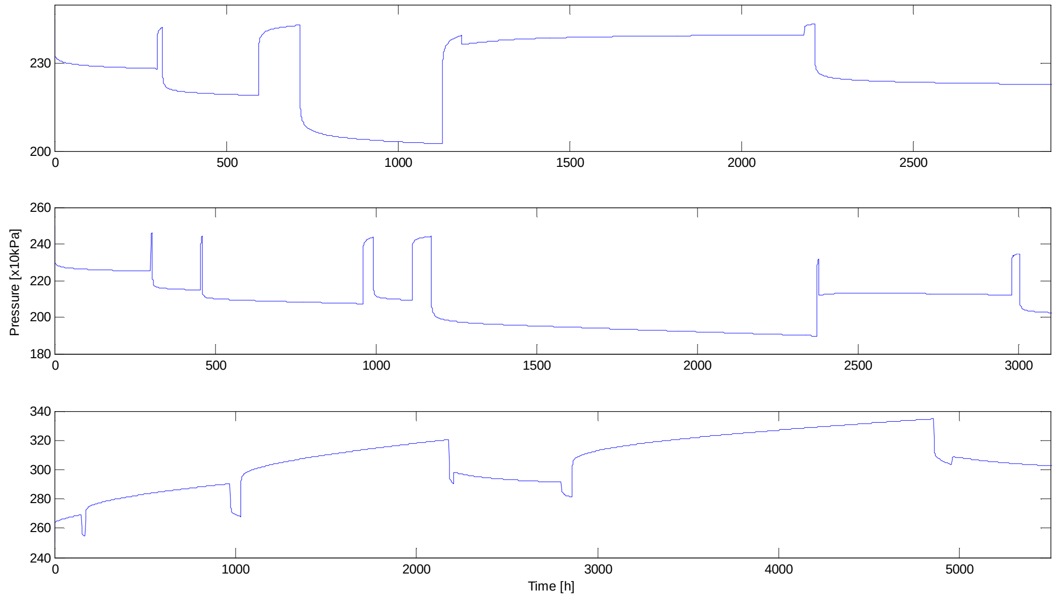

Figure 1. Pressure signals generated by the reservoir models (upper: Radial Homogeneous Infinite Acting, middle: Radial Homogeneous Closed Square with Partial Penetration, bottom: Injection Well in a Two Faults System - channel reservoir).

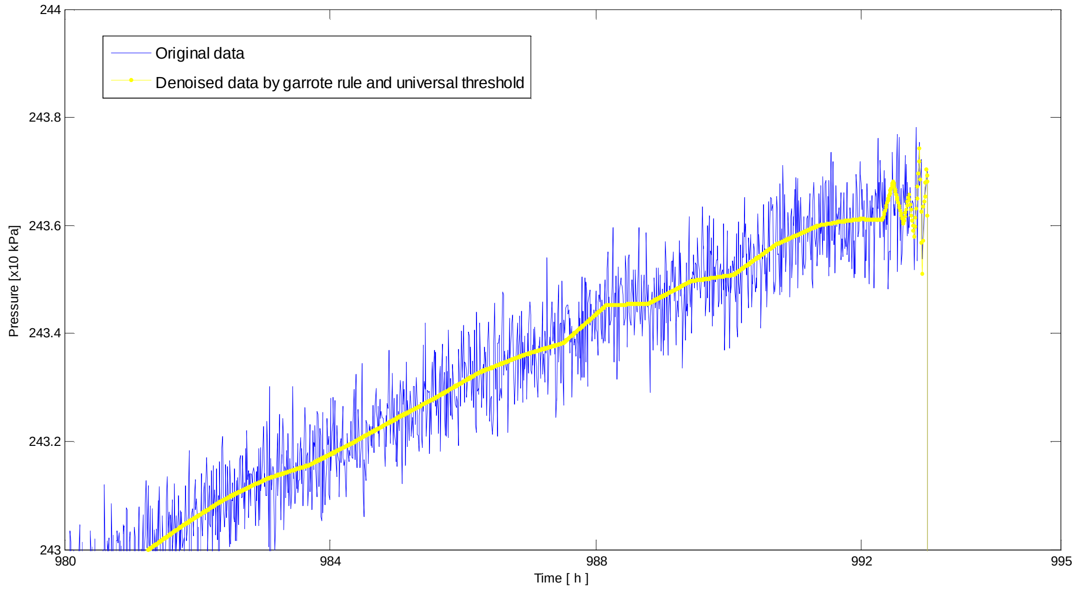

Figure 2. Comparison between the original signal (Radial Homogeneous Closed Square with Partial Penetration) and the denoised signal using biorthogonal wavelet order 26 at decomposition level 6.

The performances of each tested case are shown on table 3, which present respectively the best (B), the intermediate (I) and the worst (W) performances. The results were the same for each flow model used when Daubechies, Symmlet and Coiflet wavelet were employed.

Heterogeneous behavior was verified when biorthogonal wavelets were used, presenting the worst result when hard rule with SURE threshold was employed and best results with the garrote and SCAD rules with the universal threshold. Figure 3 shows the difference between the best and worst results achieved with biorthogonal wavelets. The use of this wavelet type is not advisable because it shows high levels of error and standard deviation.

The worst performance among all combinations was verified when the soft shrinkage with the universal threshold were employed: these combinations presented the highest error and standard deviation values. The SCAD and garrote shrinkage rules presented an intermediate performance for almost all threshold values. Finally, the best results were reached using the hard shrinkage with minimax and universal threshold, and the firm shrinkage with minimax threshold. Figures 4 and 5 show comparisons between the worst and one of the best performances.

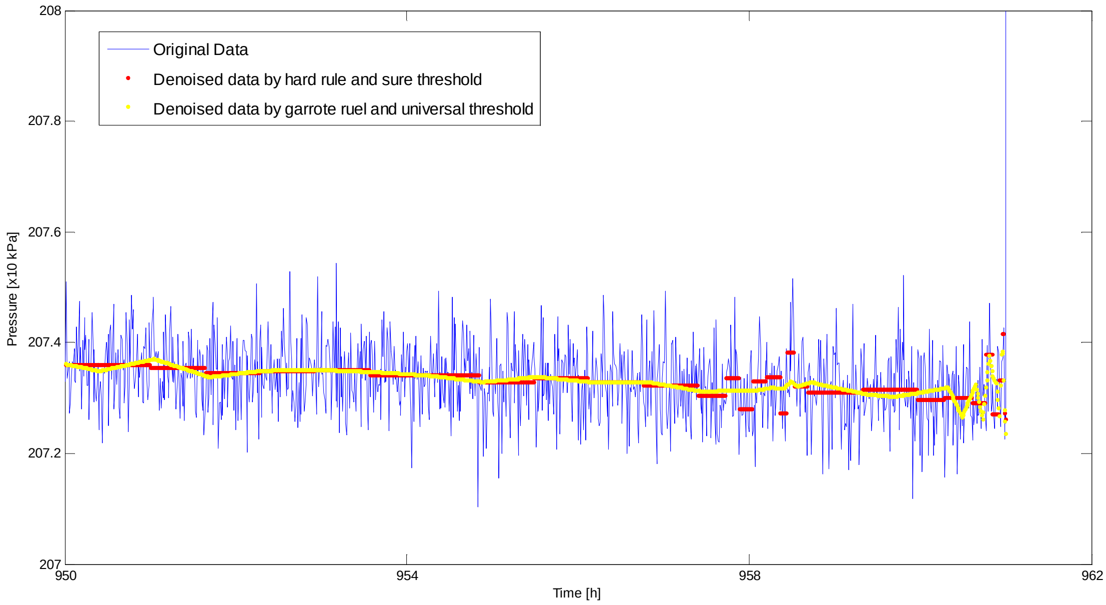

Figure 3. Comparison between the original signal (Radial Homogeneous Closed Square with Partial Penetration) and the denoised signal using biorthogonal wavelet order 13 (red) and 26 (yellow) at decomposition level 6.

Table 3. Performance of the combinations tested.

	Universal	SURE	Minimax
Soft	W	W	W
Hard	B	I	B
Firm			B
Garrote	I		I
SCAD	W		I

Observing the wavelet decomposition type and its decomposition level, the best results were shown for Daubechies 4 wavelet. After the best combinations were found, they were employed in an actual data set and compared by visual inspection. Before this process, an outlier detection routine was used to remove isolated outliers and a subsampling routine distributed the data points equally spaced in time with time step equal to 10 seconds. The test was applied on the original data using a time window, as explained before.

Applying the best combinations in the data set, it was observed that in some parts, specifically in drawdown regions, the noise as not removed efficiently (see Fig. 6). This effect could be attributed to the difference between the synthetic and real signals. In the first case, random noise with zero mean was added to the original data while for the actual PDG data the noise possibly does not present zero mean.

In build up regions, noise was satisfactorily removed, as it is shown in Fig. 7, where the denoising process preserved the sharp features of the data.

5. CONCLUSIONS

In order to determine a reliable technique for denoising PDG data, several parameters combination (wavelet decomposition type, shrinkage rule and threshold value) were studied. Furthermore, the influence of these combinations added to the choice of the decomposition level was investigated.

The tests results were classified according to their performance as best, intermediate and worst. The best results were reached using firm shrinkage rule and minimax threshold and hard shrinkage with minimax and universal threshold, for Daubechies, Symmlet e Coiflet wavelet types. The Biorthogonal wavelet presented the worst behavior, its use is not advisable. The Daubechies wavelet showed better behavior than other wavelet types, particularly at order four.

The selected methods presented satisfactory results when applied to the denoising of actual PDG data in build up regions. However, in drawdown regions of the data the chosen methods did not remove the noise as it was expected. Probably it happened due to the nature of the noise added in the synthetic data be different of that in the actual data. In the future other tests will be performed to investigate the influence of the noise type on the denoising process.

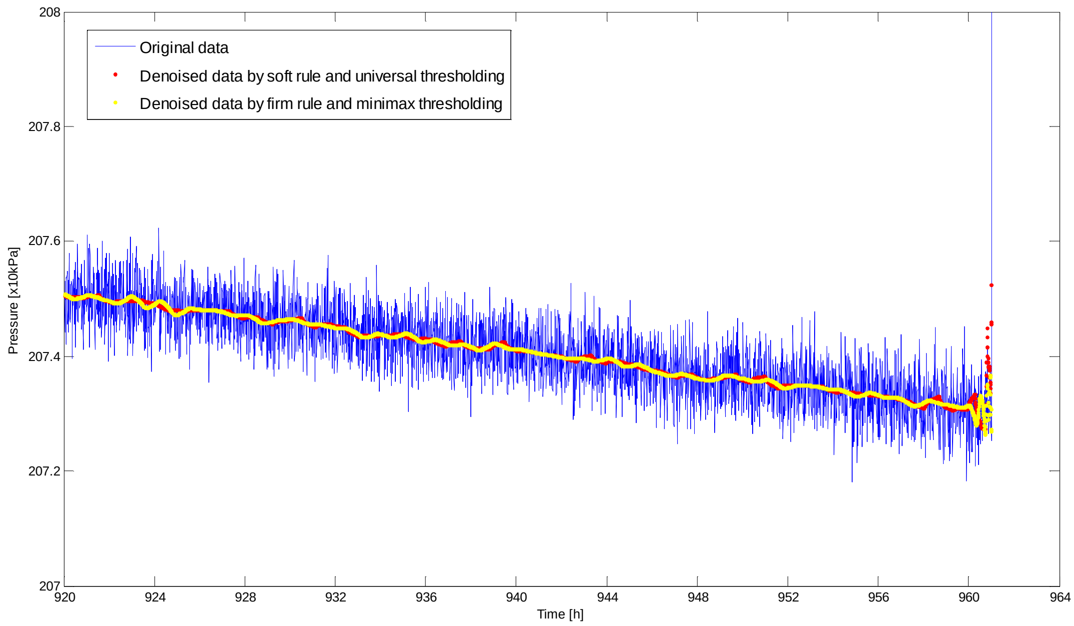

Figure 4. Comparison between the original signal (Radial Homogeneous Closed Square with Partial Penetration) and the denoised signal using Daubechies wavelet order 2 (red) and 4 (yellow) at decomposition level 6.

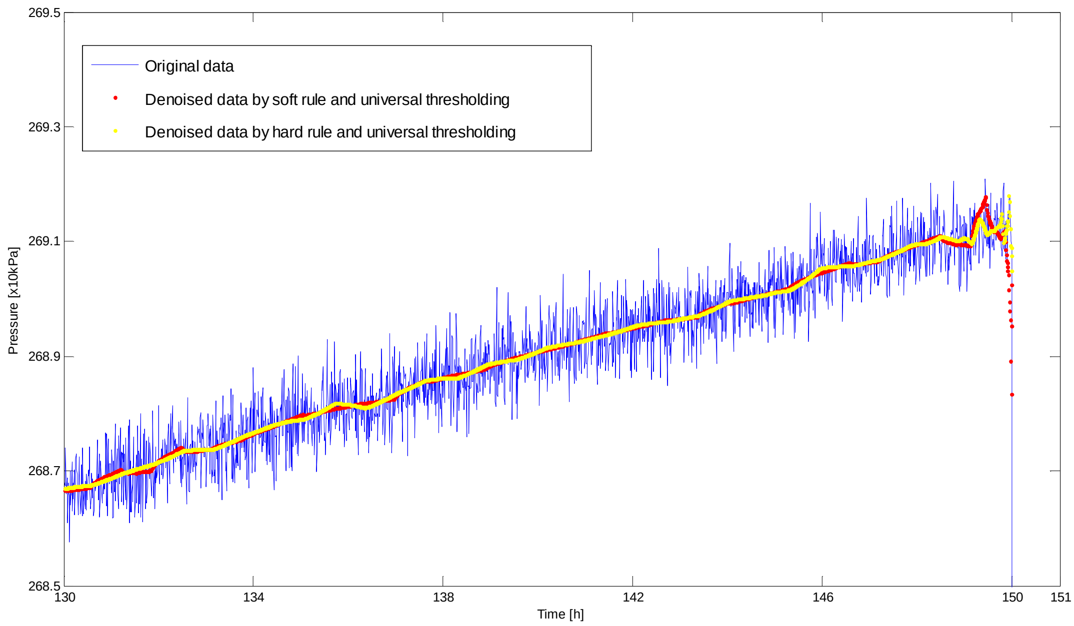

Figure 5. Comparison between the original signal (Injection well in a two faults system (channel reservoir)) and the denoised signal using symmlet wavelet order 2 (red) and 4 (yellow) at decomposition level 6.

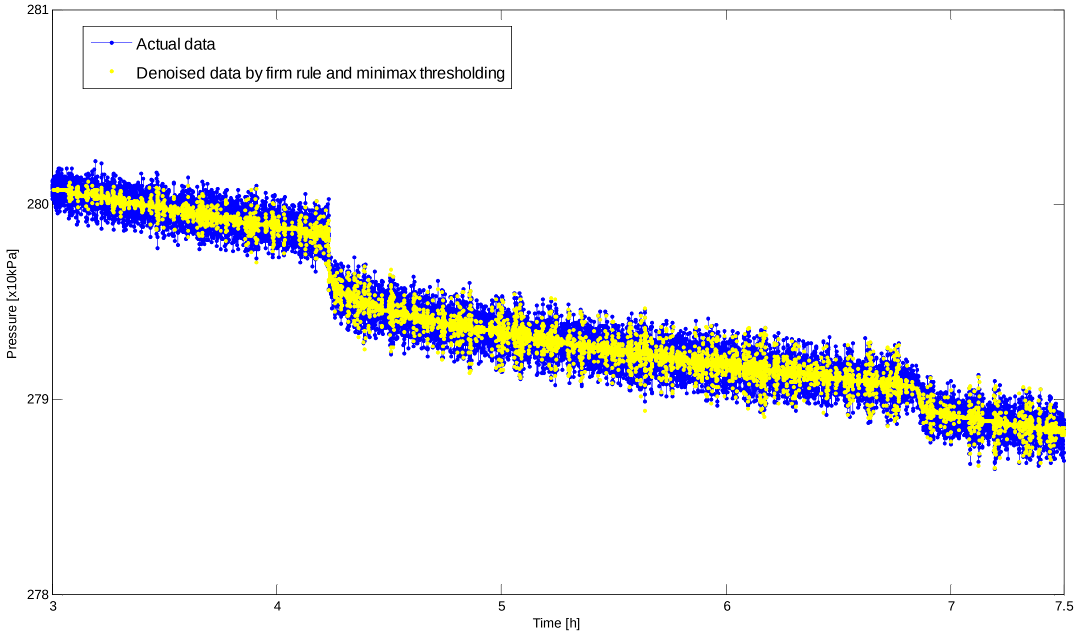

Figure 6. Comparison between actual data and the worst results obtained for the denoised data using Daubechies wavelet order 4 at decomposition level 6.

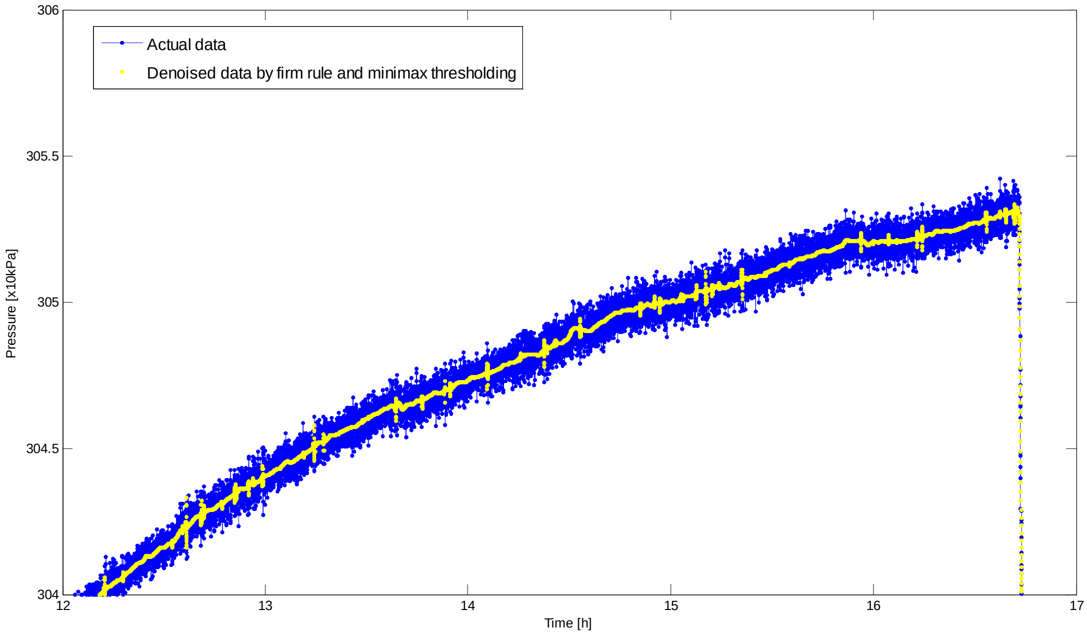

Figure 7. Comparison between the actual data and results obtained using Daubechies wavelet order 4 at decomposition level 6.

6. AKNOWLEGMENTS

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