Comparison robust data smoothing algorithms with wavelet filter for denoising sonic log signals

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Abstract

Well logging is an essential approach to making geophysical surveys and petrophysical measurements and plays a key role to interpret downhole conditions. But, well logging signals usually contain noise that distorts results and causes ambiguous interpretations. In this paper, the wavelet filter and robust data smoothing algorithms are tested for denoising synthetic sonic log and field sonic log data. Robust data smoothing algorithms include Gaussian, RLOESS (Robust locally estimating scatterplot smoothing), and RLOWESS (Robust locally weighted scatterplot smoothing) methods. Uniform and normal distribution noise applied to synthetic model and results revealed that the wavelet filter performs better than data smoothing algorithms for denoising uniform distribution noise. However, the RLOESS removed uniform noise acceptably. But, for normal distribution noise, the wavelet filter disrupts and data smoothing algorithms, specifically RLOESS attenuated noise perfectly. Due to the noise nature of field sonic log data, wavelet filter completely disrupts, but data smoothing algorithms removed the noise of field data more efficiently, particularly RLOESS. So, we can express that RLOESS is a perfect algorithm for denoising sonic log signals, regardless of noise nature.

1 - Introduction

Well logging is prominent method for recognition and realization subsurface petrophysical conditions. The main usage of well logging methods in oil exploration and exploitation industry, however used in other fields such as ore exploration and underground water exploration. The main reason of well logging technique growth is ability to recognition hydrocarbon contained layers. Well logging techniques can divide into three main categories: acoustic or sonic logs, electrical logging, and nuclear logging. In oil exploration and exploitation industry, well logging plays an essential role for imaging and realization subsurface conditions¹. But, well logging signals usually contain noise which affects the result of the geological interpretation of them. The noise is a stochastic phenomenon, which can distort the signal and affect the results of the data analysis in a bad situation. So, with the great importance of the well logging, we must attenuate noise in the well logging signals. The sonic or acoustic well logging measures the travel time of an elastic wave through the formation².

This information is also using to derive the velocity of elastic waves through the formation. The acoustic or sonic log is using to calculate the porosity, confining stress, or pore pressure of a formation if the seismic velocity of the rock matrix and pore fluid is known, which is very useful for hydrocarbon exploration³.

Well logging signal usually non-stationary signals which means that, the period and frequency of these signals not evident. The turbulence of fluids, subsurface conditions such as stress on rocks and impurities can create noise for well logging signals. During process of well logging signal, we should attenuate harmful high frequency components of signal and keep the original components of the signal⁴.

Wavelet denoising is a well-known algorithm for denoising well-logging and seismic signals^{5,6,7,8,9}. In the last decades, the wavelet transform (WT) has been used and gained acceptance in many fields and seismic data processing. Wavelet filter is invented to improve seismic signal analysis by switching from short-time Fourier analysis to new better methods to detect and analyze abrupt changes in signals. In the time-frequency analysis of the signal, the Fourier transform is lack because the Fourier transform of the signal does not contain any local information and this the main disadvantage of the Fourier transform¹⁰.

Data smoothing refers to a statistical approach of eliminating outliers from datasets to make the patterns more noticeable. The wavelet method and data smoothing algorithms are using to remove noise and predict the trend of a signal. While data smoothing can help predict trends, but it will inherently lead to less information in the sample that may lead to some data points ignored. Data smoothing and denoising are often uses synonymously, but they are fundamentally and conceptually different^{2,4,11}.

In this paper, we used robust data smoothing algorithms and wavelet transform to denoising sonic log signals. We applied data smoothing and wavelet transform for synthetic sonic log data, and then we tested these methods for the actual well-logging data. In designing synthetic sonic log data, tried actual conditions to be implemented, such as impurity, heterogeneity, and measurement noise. Finally, we compared the performance of the robust data smoothing algorithms with wavelet transform for denoising sonic log signals. The data smoothing algorithms conclude Gaussian¹², RLOESS (Robust locally estimating scatterplot smoothing), and RLOWESS (Robust locally weighted scatterplot smoothing)^{13,14,15}.

2 - Results And Discussion

For testing the data smoothing algorithm and the wavelet filter, we considered a synthetic model. This synthetic model is represented in Figure 1, and the lithology table of the synthetic model is represented in Table 1. After adding noise to the synthetic model, the wavelet filter and smoothing algorithms are evaluated for denoising the synthetic sonic log. Figure 2 shows the filtering and smoothing results of the synthetic sonic log.

Figure 2 shows that both wavelet filter and smoothing algorithms removed noise efficiently. Also, layers separation in both algorithms acceptable, but wavelet filter recognized thin layers with more surely and thin layers distinction from data smoothing algorithms is a little complicated. Also, layers separation and recognition layers boundary with wavelet filter is better than data smoothing algorithms. On the other hand, noise attenuation with data smoothing algorithms is perfectible, and noise within the independent layer is almost removed, but noise not completely attenuated within the independent layer with the use of wavelet, which can cause a pitfall in interpretations. The mentioned advantages and defects for data smoothing algorithms and wavelet filter showed as color maps in Figure3. The results in Figure 3, revealed that the layer separation of wavelet filter is better than smoothing algorithms, and layers boundary is recognizable. Precise that, the performance of the RLOESS algorithm for layer separation and boundary detection is better than Gaussian, and RLOWESS.

Note that the performance of the used methods is highly dependent on noise nature and intensity. In this case, the noise distribution is uniform (Figure 4), and for this type of noise, the wavelet filter efficiency versus data smoothing algorithms is admirable. However, the data smoothing algorithms performance is suitable, specifically RLOESS. But numerous phenomena distribution naturally is normal. So, by applying noise with a normal distribution (Figure 5), we checked the wavelet filter and data smoothing algorithms. Completely clear that, for normal distribution noise, the wavelet filter efficiency is not suitable, and abrupt fluctuation of wavelet result, causes confusion in interpretations. The oscillations of the wavelet filter within the independent layer not admissible and may interpret as different layers in a specific depth range. Due to wavelet results, separation of layers, layers boundary recognition, and clear interpretation of the result are difficult (Figure 6). For the poor noise (around zero in Figure 5), the wavelet filter can remove such poor type noise. But, with increasing noise intensity, the wavelet filter recognized high-intensity noise as the original signal oscillation. This is the main bug of the wavelet algorithm for denoising normal distribution noise. Data smoothing algorithms performance compared with wavelet filter for denoising normal distribution noise is acceptable and suitable so that layers separated almost accurately and results are interpretable. Data smoothing algorithms considering the overall signal trend for denoising. So, noise nature and intensity in the reasonable range did not affect the data smoothing algorithms performance. Note that, exceed the increase of noise causes to fade of signal trend. Accordingly, the data smoothing algorithms operation disrupts. Figure 7 shows the advantages of data smoothing algorithms and defects of wavelet filter for denoising normal distribution noise and demonstrates the overcome of data smoothing algorithms to wavelet filter for denoising normal distribution noise. Compared of data smoothing algorithms showed that the efficiency of RLOESS is better than Gaussian and RLOWESS. RLOESS performance for denoising uniform and normal distribution noise is perfect. The perfectibility of RLOESS and RLOWESS, particularly RLOESS related to the statistical operation of this algorithm, that dividing the signal into small parts and fitting the smoothed curve in these parts with considering the signal trend of each part. The main difference between RLOESS and RLOWESS is in fitted curve type that RLOESS fitted the line and parabola type curve, but RLOWESS fitted just line type curve for scattering data.

Figure 8 and figure 9 showed the performance of the data smoothing algorithms and wavelet filter for field sonic log signal denoising. The wavelet filter completely disrupts denoising field data, and the wavelet result virtually coincided with measured data, and the difference between measured data and wavelet result is not significant. But data smoothing algorithms results are cleared and precise. Due to the nature and intensity of field data noise, the wavelet filter couldn't remove the noise, and data smoothing algorithms with recognition of signal trend attenuated the noise. Due to the parabola fitting of the RLOESS algorithm, the signal details are recognized well, compared with RLOWESS and Gaussian. Likely the data smoothing results and field data subtraction represented the noise, which affected the data (Figure 10). The field data noise is normal, and due to the normal distribution of noise, the wavelet filter completely disrupts.

3 - Conclusion

We found that the RLOESS algorithm is the perfect method for denoising sonic log signals regardless of the nature of the noise. Data smoothing algorithms specifically, RLOESS is flexible for denoising sonic log signals. However, the wavelet filter is suitable for denoising uniform distribution noise. Synthetic sonic log model designed for denoising with wavelet and data smoothing algorithms. Robust data smoothing algorithms include Gaussian, RLOESS (Robust locally estimating scatterplot smoothing), and RLOWESS (Robust locally weighted scatterplot smoothing) methods. We applied uniform and normal distribution noise to the synthetic model and then checked the wavelet filter and data smoothing algorithms performance. The wavelet filter attenuates noise just when the noise is uniform and disrupts for normal distribution noise, but the data smoothing algorithms, specifically RLOESS removed noise for both types. Also, wavelet filter and data smoothing algorithms checked for denoising field sonic log data. The results revealed that the data smoothing algorithms removed noise much better, and the wavelet filter completely disrupts this case. The advantages of the RLOESS algorithm refer to its operation, that fitting parabola and liner type of curves for scatter data, and causes for better layer separation and accurate layer thickness estimation. However, the Gaussian and RLOWESS results are suitable, but in comparison, the RLOESS is perfect.

4 - Methods

4-1- Wavelet filter algorithm

The underlying model for the noisy signal is basically of the following form:

$$s(n) = f(n) + \sigma e(n) \quad \text{where } n = 0, 1, 2, \dots, N - 1$$

Where time n is equally spaced.

In the simplest model, suppose that $e(n)$ is a Gaussian white noise and the noise level σ is equal to 1.

The de-noising objective is to suppress the noise part of the signal and to recover $f(n)$. The de-noising procedure proceeds in three steps:

1- Decomposition. Choose a wavelet, and choose a level J . Compute the wavelet decomposition of the signal $s(n)$ at level J .

2- Detail coefficients thresholding. For each level from 1 to J , select a threshold and apply soft thresholding to the detail coefficients.

3- Reconstruction. Compute wavelet reconstruction based on the original approximation coefficients of level J and the modified detail coefficients of levels from 1 to J .

4-2- Data smoothing

4-2-1- Gaussian smoothing

In signal processing, a Gaussian smoothing (Also known as Gaussian blur) is typically using to reduce signal noise and reduce details. The Gaussian filter is a worldwide used filter to flatten noisy signals, and in many cases, the Gaussian filter works satisfactorily. The Gaussian function for 1D signal defined as:

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-x^2}{2\sigma^2}}$$

σ is the standard deviation of the distribution. The distribution is assumed to have a mean of 0.

4-2-2- Robust LOESS and LOWESS

Its most common methods initially developed for scatterplot smoothing are LOESS (locally estimated scatterplot smoothing) and LOWESS (locally weighted scatterplot smoothing). They are two strongly related non-parametric regression methods that combine multiple regression models in a k-nearest-neighbor-based meta-model. Both algorithms are a subset of the local regression or local polynomial regression method. Here we used robust types of LOESS and LOWESS algorithms for denoising sonic log signals. The robust type of these algorithms known as RLOESS (robust locally estimating scatterplot smoothing) and RLOWESS (Robust locally weighted scatterplot smoothing).

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Tables

Table 1. The lithology type and depth range of synthetic model

	Lithology type	Depth range (m)
1	Shale	0-200
2	Sandstone	201-300
3	Shale	301-450
4	Carbonate-anhydrite	451-500
5	shale	501-600
6	Impure sandstone	601-650
7	Carbonate	651-850
8	Salt	851-900
9	carbonate	901-1000

Figures

Figure 1

The synthetic sonic log model. The coordinate system is semi-logarithmic

Figure 2

Filtering and smoothing results of the synthetic sonic log for uniform noise. Wavelet filter comparison with (a) Gaussian smoothing, (b) RLOESS, and (c) RLOWESS. The coordinate system is semi-logarithmic

Figure 3

Compared of the main model with the results of wavelet filter and smoothing algorithms for denoising uniform noise. (a) Main synthetic model, (b) Wavelet filter result, (c) Gaussian result, (d) RLOESS result, and (e) RLOWESS result

Figure 4

(a) Uniform noise illustration, the red line is noise average, and purple dashed lines are standard deviations, (b) is noise histogram that shows the noise distribution

Figure 5

(a) Normal noise illustration, the red line is noise mean, and purple dashed lines are standard deviations,
 (b) is noise histogram that shows the noise distribution is normal. the red curve is fitted to the histogram

Figure 6

Filtering and data smoothing results of the synthetic sonic log for normal noise. Wavelet filter compared with (a) Gaussian smoothing, (b) RLOESS, and (c) RLOWESS. The coordinate system is semi-logarithmic

Figure 7

Compared of the main synthetic model with the results of wavelet filter and smoothing algorithms for denoising. (a) synthetic model, (b) Wavelet filter result, (c) Gaussian result, (d) RLOESS result, and (e) RLOWESS result

Figure 8

Compared wavelet filter and data smoothing algorithms for denoising field sonic log data. (a) The field data, (b) Wavelet filter result, (c) Gaussian result, (d) RLOESS result, (e) RLOWESS result. The coordinate system is semi-logarithmic

Figure 9

Compared the wavelet filter with data smoothing algorithms performance for denoising field sonic log data. (a) Field sonic log data, (b) Wavelet result, (c) Gaussian result, (d) RLOESS result, (e) RLOWESS result

Figure 10

Subtraction histogram of (a) Gaussian result and field data, (b) RLOESS result and field data, (c) RLOWESS result and field data. the red curve fitted to histograms