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Spectral Noise Logging Data Processing Technology

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Abstract

Rational development of oil and gas reservoirs is possible only with efficient monitoring by various well logging techniques. This paper presents algorithms for processing data acquired by spectral noise logging (SNL) in memory mode. The SNL technology is designed to identify flowing reservoir intervals, cross-flows behind casing and tubing and casing leaks by spectral analysis of recorded noise signals.

While moving through a reservoir, fluids and gases create turbulence and rock vibrations that in turn generate noise. This acoustic noise is recorded with a noise logging memory tool consisting of a high-sensitivity piezoelectric hydrophone sensor and an amplifier and data collection module. The tool records acoustic signals in the frequency range of 15 Hz to 60 kHz. The existing SNL technology excludes intense broadband noise created by the movement of the tool in the well.

Useful information is extracted from background noise using a technique based on wavelet thresholding. Spectral noise density in the depth-frequency plane undergoes a wavelet transform. At each measurement depth, several tens of noise signals are recorded to determine mean wavelet coefficients and their typical variance. Then, they are analysed to remove statistically insignificant details from the signal spectrum and to suppress noise components that are present throughout large depth intervals.

The processing of data acquired in tens of wells from various fields has shown that the noise features identified by wavelet filtering correlate with open-hole data and are confirmed by conventional well logging techniques.

Introduction

The concept of recording acoustic noise in wells dates as far back as 1955 when Enright (1955) qualitatively described the procedure of locating tubing and casing leaks with an acoustic recorder detecting the highest noise levels at leaks. Korotaev et al. (1970) used a noise detector to identify gas-bearing zones in uncased wells. Prof. McKinley (1994) introduced a noise logging technology based on the recording of acoustic noise into several frequency channels and presented the results of his own experimental research. Despite the ever-growing use of such tools, noise logging data were long considered untrustworthy and difficult to interpret. The successful development of precision downhole equipment led to the creation of an acoustic noise logging tool with the piecewise continuous recording of acoustic noise and the spectral analysis of well noises in wide frequency ranges (Aslanyan 2010).

Qualitative and quantitative analyses of SNL data require filtering techniques that can extract statistically significant spectral components, while the useful signal is expected to be confined to a narrow permeable reservoir interval. This paper presents a modified method of wavelet thresholding to remove from the spectrum statistically insignificant features impeding qualitative interpretation. Data filtering for several wells is given as an example to illustrate the advantage of this algorithm over universal wavelet filtering techniques. It has also been shown that the noise features identified by filtering correlate with open-hole logging data and are confirmed by conventional well logging techniques.

SNL data filtering techniques

SNL data are processed and visualised in the spectral domain. The Fourier transform is used to assess the noise power spectral density (Oppenheim 1989). The spectra are averaged for each station and shown in frequency-depth colour panels that visualise noise amplitudes. Then, two-dimensional noise power spectral densities are visually analysed for intense spectral features that will be used for data interpretation. The presence of noise in the input signal spectrum may hinder the delimitation and characterisation of a flowing reservoir interval. Various filtering techniques based on wavelet transform can be used to identify such features confined to narrow depth intervals.

Universal wavelet thresholding algorithm

Today, wavelet thresholding algorithms have come into wide use (Antoniadis 1995). In such algorithms, signals are represented by sets of wavelet coefficients corresponding to different basis function scales. Empirically determined sets of wavelet coefficients are assessed for noise levels and statistical significance by checking their absolute values against a certain threshold. Noise levels in universal wavelet filtering algorithms are normally determined by analysis of the variance of wavelet coefficients corresponding to one basis function scale but different instants or different 2D image areas (Donoho 1995). Universal wavelet filtering algorithms can be used to filter the averaged power spectral densities. Filtering algorithms for two-dimensional data undergo fast development, mostly because of image processing demands. Normally, local statistical characteristics of illumination variation weakly depend on the direction. In contrast, the noise power spectral density changes gradually between neighbouring frequencies at a certain depth, but can change sharply between neighbouring depths. Another difference is that the intensity of uninformative noise can vary significantly with frequency (increasing at lower frequencies) and depth, whereas the average characteristics of image noise remain constant.

Fig. 1 below shows an example of applying universal filtering algorithms to noise logging data (2D stationary wavelet transform). The denoising procedure was based on the Donohoe-Johnston paradigm and threshold selection using Stein's unbiased risk estimate (Mallat 1989).

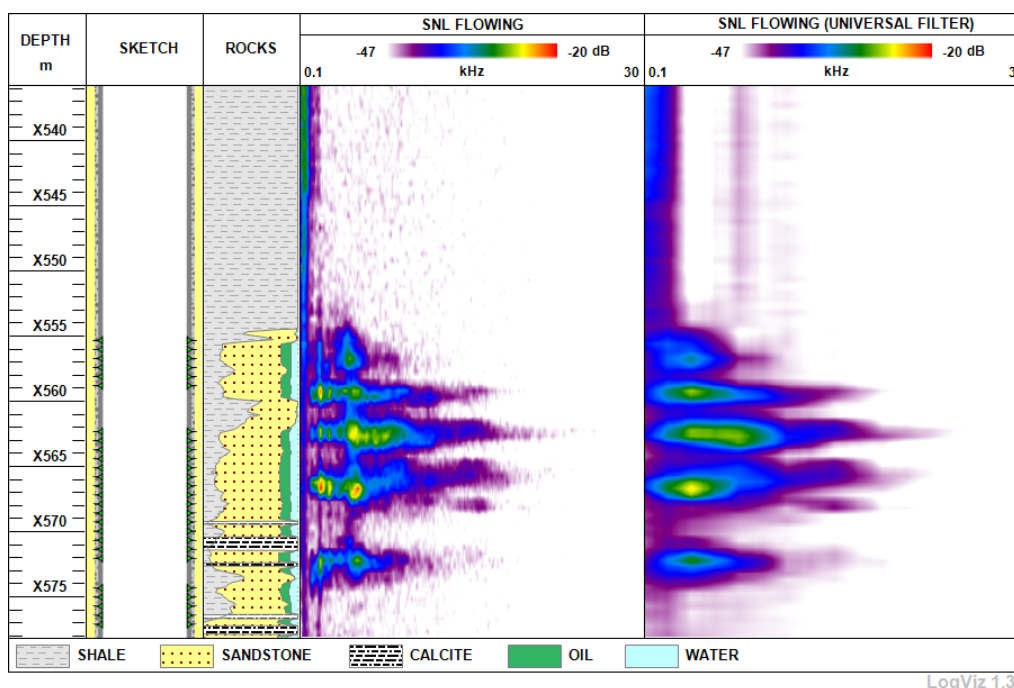


Fig. 1. An application of a universal wavelet thresholding algorithm, with the averaged noise power spectral density on the left panel and that after filtering on the right one.

Filtering is seen to cause some blurring that also occurs with other thresholds and is proportional to the degree of filtering and smoothing. Thus, it is recommended to use special filtering algorithms that take into account the specific characteristics of analysed data. Given below is a wavelet thresholding algorithm taking into account spectral noise logging data features.

Modified wavelet thresholding algorithm

A number of signal sequences recorded during stationary measurements can be used to both determine mean noise spectral density at each depth and at the same time filter the signals to extract the most statistically significant one. Useful information is extracted from background noise by a technique employing the above wavelet thresholding algorithm. As decisions on whether to consider a signal statistically significant are made through the analysis of signal variation at each station, noises that are caused by random fluctuations and can be misinterpreted are filtered from spectral noise logs. This algorithm is described in more detail in Appendix 1.

Low-frequency noise is a particular challenge to the interpretation of acquired SNL data. Such noise normally occurs in large depth intervals, whereas permeable reservoirs only in narrow ones. The modified wavelet thresholding algorithm excludes this noise because it makes only a minor contribution to wavelet coefficients and can be filtered at a determined threshold.

Thus, the above wavelet filtering procedure excludes random noise from the noise spectrum. The filtered noise logs are more contrast and better display low-intensity details that were previously masked by background noise.

SNL data filtering cases

The cases below illustrate the application of a modified wavelet thresholding algorithm and show how spectrum details found by filtering correlate with logs recorded using other techniques, for instance, with open-hole and corrosion logs.

Case 1. Extraction of a useful signal from low-frequency noise

Fig. 2. illustrates an application of wavelet thresholding and shows a low-frequency high-amplitude signal, detected at all depths, that was mainly generated by wellbore flow. Filtering can minimise this noise, as shown in the right-side panel of Fig. 2. After filtering, noise at a depth of X582 m was considered statistically insignificant, unlike statistically significant 2–5 kHz low-intensity noise detected at a depth of X562 m. Broadband noise from the depth interval X554–X558 m and noise from a depth of X562 m correlate with porous reservoir zones identified by open-hole logging and most probably containing fluid flows. Reservoir flows were detected only in the two upper perforated intervals, which indicated that no flow occurred in other ones. This case demonstrates how a wavelet filtering algorithm can increase the contrast in noise spectral density and exclude statistically insignificant noise that can hinder the interpretation of noise logs.

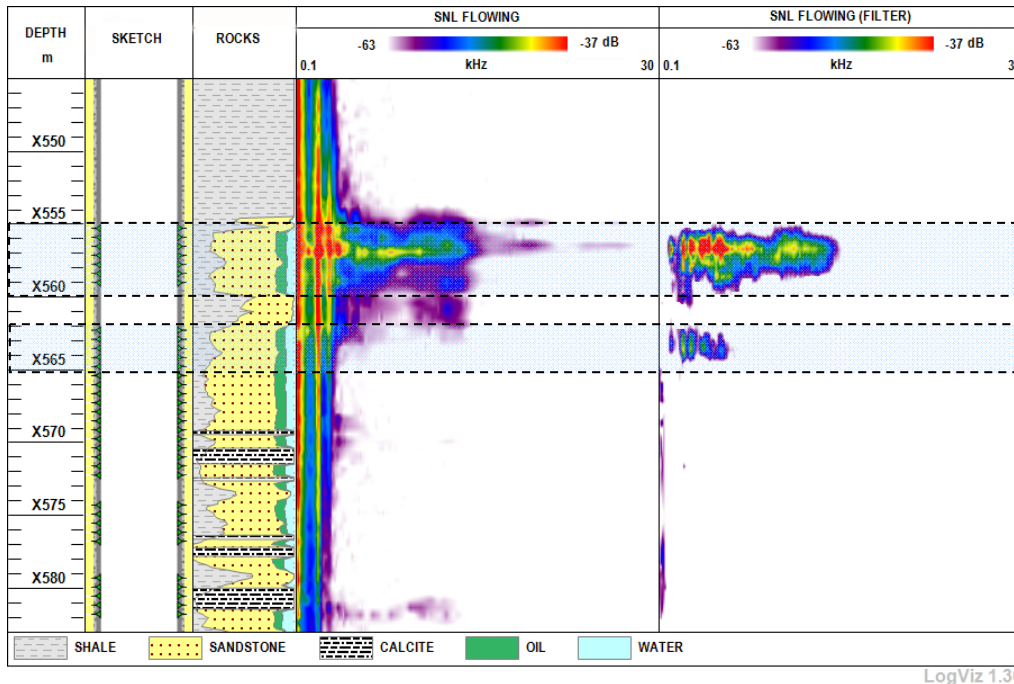


Fig. 2. An application of a wavelet thresholding algorithm, with the arithmetically averaged noise power spectral density on the left-side panel and that after wavelet filtering on the right-side one.

Case 2. Extraction of a useful signal from broadband noise

This case provides another example of SNL data filtering using the above method. The panel of arithmetically averaged noise spectral density displays intense broadband noise that hinders the extraction of useful information on reservoir flow. The modified wavelet threshold filter has been employed to average and filter SNL data. The filtering results are shown in the right-side panel of Fig. 3. The figure shows broadband noise detected in a large depth interval and found statistically insignificant and broadband noise spots that appeared in perforated zones at X565 m and X567–X570 m. Open-hole logging data confirmed the presence of a reservoir in this zone.

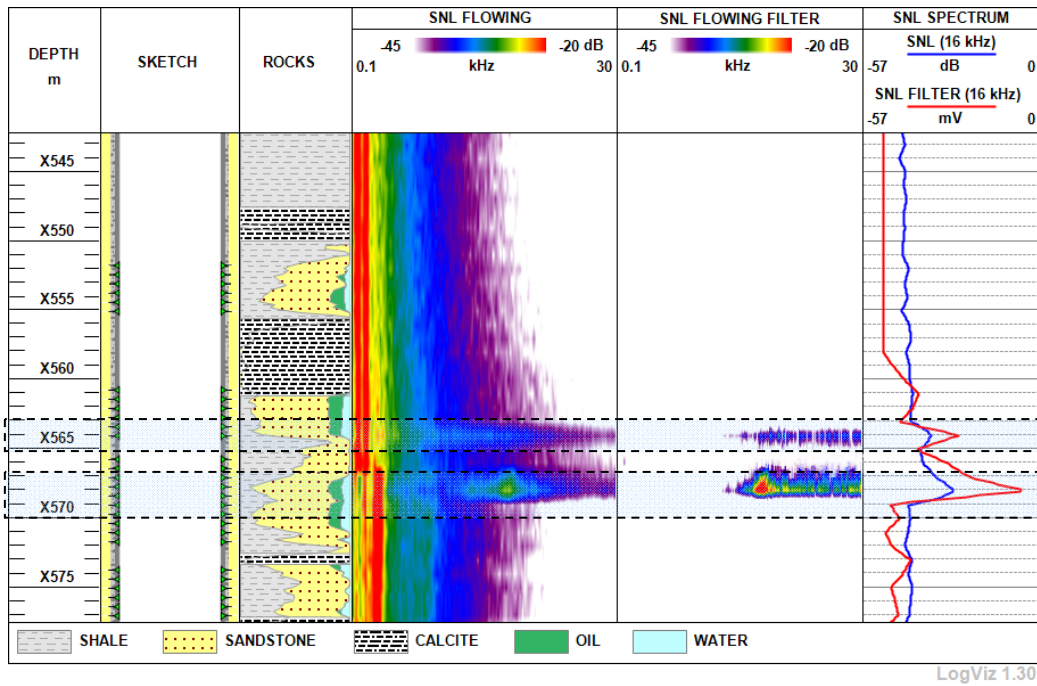


Fig. 3. ESP noise filtering results, with noise spectral density before filtering (SNL FLOWING) and after filtering (SNL FLOWING FILTER) and noise spectral density at 16 kHz before filtering (SNL) and after filtering (SNL FILTER).

Case 3. Detection of casing leaks against an acoustic noise background

Operating oil and gas wells are prone to accidental mechanical damage due to various factors including sulphur-containing fluids and poor cement bonds that can cause leaks and premature breakdown.

There are numerous downhole corrosion logging methods to detect leaks and metal loss. Spectral noise logging can be effectively combined for this purpose with magnetic imaging defectoscopy (MID) and high-precision temperature logging (Aslanyan 2012).

The figure below shows the results of noise logging data filtering using a modified wavelet filter. Filtering clearly revealed noise at X495 m depth correlating with a decrease in casing wall thickness detected by magnetic imaging defectoscopy. Noise detected in an unperforated porous interval indicated a casing leak.

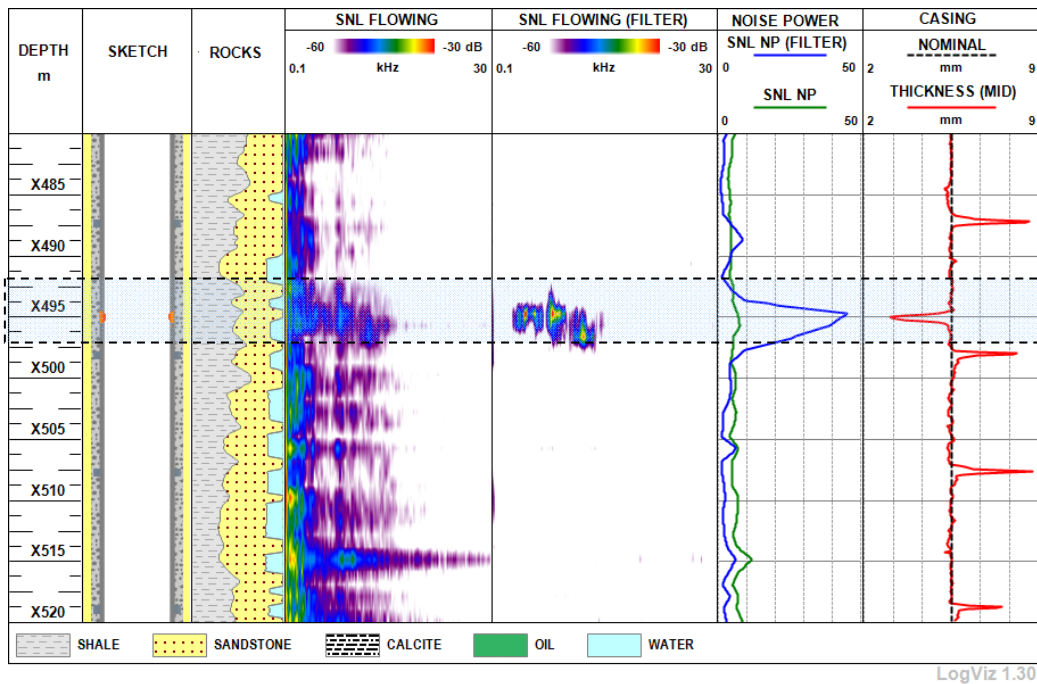


Fig. 4. Detection of a casing leak using a modified wavelet thresholding algorithm. The main data panels are noise spectral density before filtering (SNL FLOWING) and after filtering (SNL FLOWING FILTER), integral noise power (NOISE POWER) and casing wall thickness (CASING THICKNESS).

Conclusion

The filtering of spectral noise logging data from various wells has shown that the proposed modification of wavelet thresholding can effectively exclude statistically insignificant features from the noise spectral density and enhance its contrast. The filtering results correlate with open-hole logging data, and the signals extracted from the spectrum are confined to permeable reservoir intervals.

It has also been shown that this filtering algorithm is effective for processing downhole defectoscopy data. Leak-related noises identified by filtering correlate with corroded areas of the casing detected by the corrosion logging tool.

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Appendix 1

Modified wavelet thresholding algorithm

Initially, noise spectral density $S_{f,d}$ in the depth-frequency plane undergoes discrete wavelet decomposition in depth for each frequency. The basis function of the wavelet transform, $\psi_{j,k}(d)$ wavelet, is a fluctuation of the typical scale j at the depth k . Wavelet decomposition coefficients can be written as $C_{j,k}^f = \sum_d S_{f,d} \psi_{j,k}(d)$.

Thus, the coefficient $C_{j,k}^f$ reflects the fluctuation of noise spectral density at the frequency f , typical depth scale k and depth j . SNL records several tens of noise signal sequences at each measurement depth to determine mean wavelet coefficients $\langle C_{j,k}^f \rangle$ and the typical scale of their variance, for instance standard deviation $\sigma_{j,k}^C = \sqrt{D\langle C_{j,k}^f \rangle}$.

Then, the statistical significance of wavelet decomposition coefficients is assessed with a two-sided test on the following two versions of the statistical hypothesis:

1) $\left| \langle C_{j,k}^f \rangle \right| < T_{j,k} \Rightarrow H_0 : M C_{j,k}^f = 0$: If the absolute value of the ensemble average does not exceed a certain threshold, $T_{j,k}$, the hypothesis of statistical significance of the coefficient is rejected and this coefficient is equated to zero.

2) $\left| \langle C_{j,k}^f \rangle \right| \geq T_{j,k} \Rightarrow H_1 : M C_{j,k}^f \neq 0$: If the absolute value of the ensemble average exceeds a certain threshold, $T_{j,k}$, the hypothesis of statistical significance of the coefficient is not rejected.

The $T_{j,k}$ threshold can reasonably be made proportional to the standard deviation of the selected wavelet coefficient $T_{j,k} = \sigma_{j,k}^C z_\alpha$

where z_α is a proportionality coefficient common to all wavelet coefficients. Thresholding of wavelet coefficients is followed by wavelet reconstruction.

The selection of z_α value can be based on various reasons, for instance, on the fact that the distribution of sample means of wavelet coefficients $\langle C_{j,k}^f \rangle$ is close to normal. A significance level α (the maximum permissible percentage of erroneous solutions) is set and the threshold is determined from the following formula:

$$\int_{z_\alpha}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx = \frac{\alpha}{2}$$

For instance, if $\alpha = 0.05$, the coefficient $z_\alpha = 1.96$. Thus, the user can select significant components in the noise spectral density by setting a significance level and varying the threshold.