Study on the Logging while Drilling Data Correction Method based on Wavelet Denoising

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Abstract

LWD can be used to measure the geological environment. However ,there is a high error in the measured data due to the influence of system factors, it can not reflect the underground geological environment accurately, so the research on the system of drilling measuring instrument calibration method, using the method of wavelet threshold denoising to achieve the real-time correction of the system influence factors in logging data,effectively solve the problem of data error of geological risk monitoring and analysis.

Keywords

LWD, System Error, Wavelet Denoising, Real-Time Correction.

1. Introduction

Geological risk problems often encountered in drilling operation,the drilling risks mainly include the risk of lost circulation, well fall risk, the risk of wells flow, andsticking risk.These four types of risks are mainly caused by the unknown geological environment.In the process of the geological information measurement by LWD, there is a large error and interference in the measurement information, so the establishment of a set of correction system for LWD system influence factors is particularly important,In this paper, we use wavelet threshold denoising to carry out correlation correction model for the influence of LWD data, and evaluate the effect of wavelet threshold denoising to prove its feasibility.

2. Analysis of wavelet threshold denoising method

There are many errors in LWD data from the system itself, such as the influence factors of the sensor. There are periodic, trend and random items in non-stationary signals,but the three are different in time scale, the fundamental component of wavelet threshold denoising is to decompose signals and compositions at different time scales, it can achieve effective denoising [1][2][3].

The basic function of wavelet threshold denoising hasgreat flexibility, it can obtain high frequency signal with a shorter time, so it allows more accurate description of the small range, suitable for the processing of instantaneous noise .Wavelet analysis provides a more accurate approach for noise processing, suitable for correction of the system influence factors in logging data.

In the process of denoising, through the wavelet decomposition of the original signal, to establish a suitable threshold function, remove the signal which is less than the threshold value, and retain the signal which is greater than the threshold, so that the noise signal has been processed.At last, the original signal is synthesized by wavelet, and the effective part of the signal is preserved[4].The specific analysis process is as follows:

(1)The LWD logging signal is decomposed by wavelet to extract the information of different scales;

(2) By selecting the appropriate threshold function, establish the data processing rules, retain the signal which is greater than the threshold, and remove the signal which is less than the threshold value,to keep the true signal and eliminate noise.

(3) The real signal after processing is preserved, and the original signal is reconstructed by wavelet inverse transform, this is the LWD data after the system calibration.Wavelet denoising flow chart shown in figure 1.

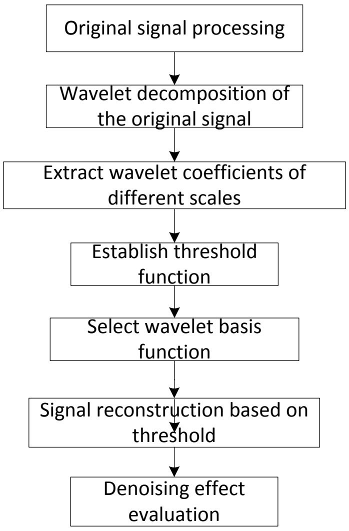

Figure 1. Wavelet denoising flow chart

3. Establishment of wavelet threshold denoising correction model

The threshold function includes two kinds, one is the soft threshold, the other is the hard threshold (fixed threshold), we choose the soft threshold as the threshold of wavelet threshold denoising through the optimization considering.The soft threshold denoising curve will show good smoothness and continuity, and ensure the accuracy of the data. The expression is as follows[5][6]:

$$\widehat{W}_{j,k} = \begin{cases} \operatorname{sgn}(W_{j,k})(W_{j,k} - \lambda), & \left|W_{j,k}\right| \geq \lambda \\ 0 \qquad , & \left|W_{j,k}\right| < \lambda \end{cases} \tag{1}$$

For the selection of wavelet basis function, there are four factors:vanishing moment order, regularity, compactness and orthogonality. There are many high frequency noise in LWD data, so the high order vanishing matrix will be better to deal with the data, so considering Daubechies as the wavelet basis function.The Daubechies wavelet function is used as the wavelet base function of the LWD data system correction, and the signal decomposition and reconstruction of the basis function is usually based on the Mallat algorithm:

For the signal $f(t)$, projected on a scale space V_j ,the general information expression can be obtained [7]:

$$f_s^j(t) = \sum_k c_{j,k} * \varphi_{j,k}(t), \qquad k \in Z \tag{2}$$

In the formula (2), j is the decomposition scale, $c_{j,k} = \left\langle f(t), \phi_{j,k}(t) \right\rangle$ is the scale expansion coefficient of signal, $\phi_{j,k}(t)$ is the orthonormal basis functions in scale space.

$$\begin{aligned} \phi_{j,k}(t) &= 2^{-j/2}\phi(2^{-j}t - k) = 2^{-(j-1)/2}\sum_{n\in Z} h_0(n)\phi(2^{-(j-1)}t - 2k - n) \\ &= 2^{-j/2}\sum_{m\in Z} h_0(m-2)\phi(2^{-(j-1)}t - m) \\ &= \sum_{m\in Z} h_0(m-2k)\phi_{j-1,m}(t) \end{aligned} \tag{3}$$

Simultaneous (2) (3), the scale expansion coefficient of the signal can be obtained:

$$\begin{aligned} c_{j,k} &= \int_R f(t)\phi_{j,k}(t)dt = \int_R f(t)[\sum_{m\in Z} h_0(m-2k)\phi_{j-1,m}(t)] \\ &= \sum_{m\in Z} h_0(m-2k)\int_R f(t)\phi_{j-1,m}(t) \\ &= \sum_{m\in Z} h_0(m-2k)c_{j-1,m} \end{aligned} \tag{4}$$

The function $f(t)$ can be projected on the wavelet space W_j , and the detail information expression can be obtained:

$$f_d^j(t) = \sum_k d_{j,k}\psi_{j,k}(t), \qquad k\in Z \tag{5}$$

In the formula (5), $d_{j,k}$ is the wavelet expansion coefficient of signal $f(t)$, $\psi_{j,k}(t)$ is the wavelet function of scale j.

$$\begin{aligned} \phi_{j,k}(t) &= 2^{-j/2}\phi(2^{-j}t-k) = 2^{-(j-1)/2}\sum_{n\in Z} h_0(n)\phi(2^{-(j-1)}t-2k-n) \\ &= 2^{-(j-1)/2}\sum_{m\in Z} h_0(m-2k)\phi(2^{-(j-1)}t-m) \\ &= \sum_{m\in Z} h_0(m-2k)\phi_{j-1,m}(t) \end{aligned} \tag{6}$$

Simultaneous (5) (6), the scale expansion coefficient of the signal can be obtained:

$$d_{j,k} = \sum_{m\in Z} h_1(m-2k)c_{j-1,m} \tag{7}$$

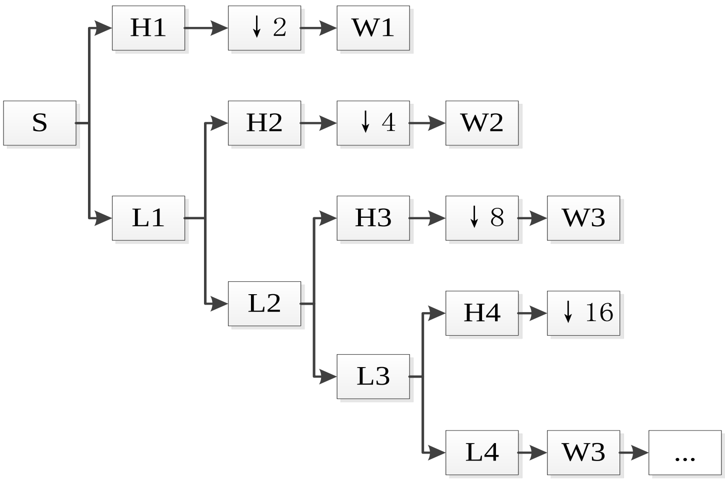

Figure 2. Wavelet decomposition process

According to the decomposition coefficients $W_n, L_n, ..., L_2, L_1$ in Figure 2,taking reverse deduction of the wavelet,which is the Mallat reconstruction method, and its reconstruction expression can be expressed as [8]:

$$\sum_{m\in Z} c_{j-1,m}\phi_{j-1,m} = \sum_{m\in Z} c_{j,m}\phi_{j,m} + \sum_{m\in Z} d_{j,m}\psi_{j,m} \tag{8}$$

Multiplying both sides of the formula (8) by $\phi_{j-1,k}$:

$$\left\langle \sum_{m\in Z} c_{j-1,m}\phi_{j-1,m}, \phi_{j-1,k} \right\rangle = \left\langle \sum_{m\in Z} c_{j,m}\phi_{j,m}, \phi_{j-1,k} \right\rangle + \left\langle \sum_{m\in Z} d_{j,m}\phi_{j,m}, \phi_{j-1,k} \right\rangle \tag{9}$$

Thus:

$$c_{j-1,m} = \sum_{m \in Z} c_{j,m} \left\langle \phi_{j,m}, \phi_{j-1,k} \right\rangle + \sum_{m \in Z} d_{j,m} \left\langle \phi_{j,m}, \phi_{j-1,k} \right\rangle \tag{10}$$

Because that:

$$\left\langle \phi_{j,m}, \phi_{j-1,k} \right\rangle = \left\langle \sum_{m \in Z} h_0(k-2m)\phi_{j-1,k}, \phi_{j-1,k} \right\rangle = h_0(k-2m) \tag{11}$$

$$\left\langle \psi_{j,m}, \phi_{j-1,k} \right\rangle = \left\langle \sum_{m \in Z} h_1(k-2m)\phi_{j-1,k}, \phi_{j-1,k} \right\rangle = h_1(k-2m) \tag{12}$$

Taking the formula (11) (12) into the formula (10) can be used to reconstruct the effective signal after denoising:

$$c_{j-1,m} = \sum_{m \in Z} (c_{j,m} h_0(k-2m)) + d_{j,m} h_1(k-2m) \tag{13}$$

4. Comparative analysis

(1)Software design. The software of wavelet threshold denoising is developed, which can be used for real-time automatic correction of LWD data.Taking into account the expanding application of different conditions, taking the wavelet basis type, analysis and reconstruction layer and threshold function as variable. There are six types of wavelet base in software integration: fixed threshold criterion, minimax criterion, Stein unbiased likelihood estimation criterion, Heursure threshold criterion and soft threshold.

(2)Simulation application.Taking the logging data of X1 well as an example.This paper analyzes the real-time wavelet threshold denoising of several key logging parameters, including the resistivity of drilling while drilling, the acoustic logging while drilling, and the natural gamma-ray while drilling.The correction results are shown in Figure 3, the left is the overall analysis, and the right is the local magnification analysis.

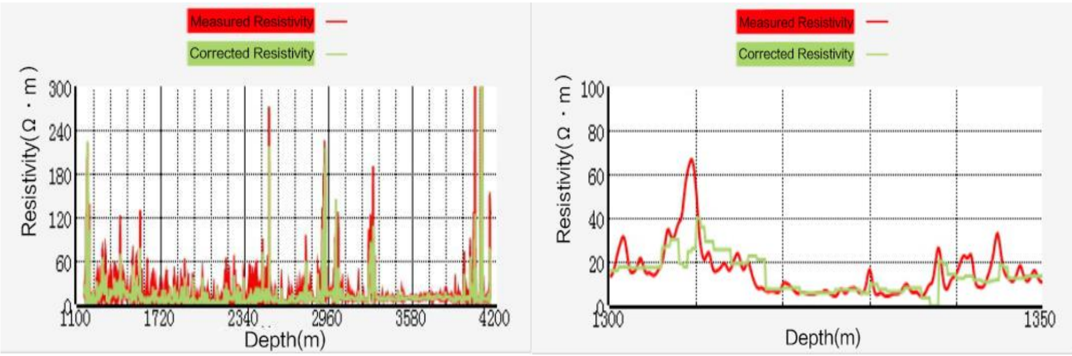

Figure 3. Wavelet threshold denoising result of LWD resistivity

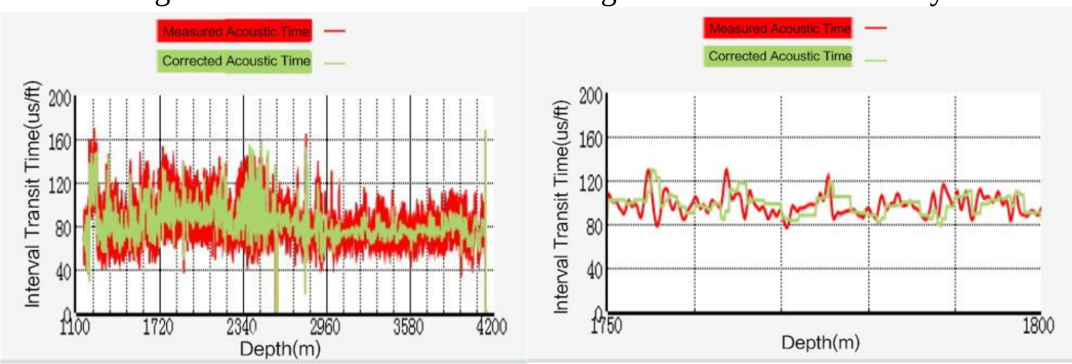

Figure 4.Wavelet threshold denoising result of LWD acoustic wave

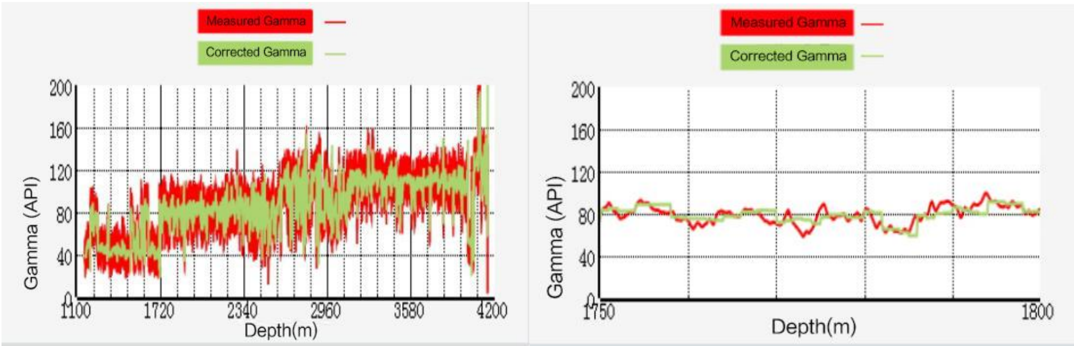

Figure 5. Wavelet threshold denoising result of LWD gamma

It is necessary to evaluate the effect of logging data after wavelet threshold denoising.In this paper, three kinds of evaluation methods, such as signal to noise ratio (SNR), signal to noise ratio (SNR) gain and root mean square error (Daubechies), are considered,the wavelet basis function selection is Daubechies wavelet, using 3 layer decomposition.According to the results of calculation and analysis, it is concluded that the performance of the three drilling parameters, LWD resistivity, LWD acoustic wave and LWD gamma obtained by wavelet threshold denoising, as shown in table 1.

Table 1. Wavelet threshold denoising performance

LWD resistivity logging						
	Moving average filter	Default threshold (10)	Default threshold (20)	Default threshold (30)	Default threshold (40)	soft threshod
SNR	8.6363	23.2545	20.1166	8.6362	17.2604	27.1286
RMSE	13.8344	2.5596	3.6733	13.8344	5.1035	1.6385
LWD acoustic wave logging						
	Moving average filter	Default threshold (10)	Default threshold (20)	Default threshold (30)	Default threshold (40)	soft threshold
SNR	24.1599	27.0685	24.4192	23.2148	22.5382	30.7831
RMSE	5.2266	3.7393	5.0702	5.8243	5.8243	2.4382
LWD gamma logging						
	Moving average filter	Default threshold (10)	Default threshold (20)	Default threshold (30)	Default threshold (40)	soft threshold
SNR	26.4610	28.1933	25.6588	24.4765	23.7849	31.6895
RMSE	4.3395	3.5562	4.7612	5.4554	5.9075	2.3778

We can see that the default threshold is better than moving average filter from the table, and the given soft threshold is better than the default threshold, indicates that the wavelet threshold denoising method is feasible, and the method is simple, has a small amount of calculation, and the actual engineering is widely used.

5. Conclusion

(1)Considering the system influence of LWD data can reduce the measurement error,in order to accurately reflect the underground geological environment, it can reduce the probability of risk occurrence.

(2)Through the study of MWD system calibration methods, using thewavelet threshold denoising to correct the system influence of LWD data,there are 6 types of wavelet bases and 5 kinds of threshold function types, which can be optimized according to the actual situation or data types.In order to achieve the real-time correction of the system influence factors of LWD data.

(3)Through the application of LWD data simulation and evaluation of wavelet threshold denoising results,it is proved that the wavelet threshold denoising model and method can be used to correct the LWD data.

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