Research on De-noising of Downhole Engineering Parameters by Wavelet based on Improved Threshold Function

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Abstract—The measurement of downhole engineering parameters is greatly disturbed by the working environment. Effective de-noising methods are required for processing logging-while-drilling (LWD) acquisition signals, in order to obtain downhole engineering parameters accurately and effectively. In this paper, a new de-noising method for measuring downhole engineering parameters was presented, based on a feedback method and a wavelet transform threshold function. Firstly, in view of the mutability and density of downhole engineering data, an improved wavelet threshold function was proposed to de-noise the signal, so as to overcome the shortcomings of data oscillation and deviation caused by the traditional threshold function. Secondly, due to the unknown true value, traditional single denoising effect evaluation cannot meet the requirements of quality evaluation very well. So the root mean square error (RMSE), signal-to-noise ratio (SNR), smoothness (R) and fusion indexs (F) are used as the evaluation parameters of the de-noising effect, which can determine the optimal wavelet decomposition scale and the best wavelet basis. Finally, the proposed method was verified based on the measured downhole data. The experimental results showed that the improved wavelet de-noising method could reduce all kinds of interferences in the LWD signal, providing reliable measurement for analyzing the working status of the drilling bit.

B

I. INTRODUCTION

ecause of the complications in the stratum structure, accidents during the petroleum exploration and development process are a problem that cannot be ignored. One of the main reasons for these accidents is that the downhole engineering parameters cannot be obtained accurately [1]. The downhole engineering parameters measuring system is vulnerable to the downhole environment. Several factors can result in interference, such as high temperature, high pressure and strong vibration caused by assorted noise. In this case, the obtained data cannot reflect the true working conditions of the downhole. The key to better conduct the drilling test is to obtain accurate drilling pressure and torque from various interfered signals, which are known as the logging-while-drilling (LWD) acquisition signals. To make sure that the drilling environment is safe, it is important to establish an effective de-noising method to obtain real drilling pressure, torque, and other downhole engineering information.

During past decades, researchers have put forward a lot of methods to deal with de-noising processing for downhole engineering parameters. Namuq [2] combined a linear filter algorithm method with a nonlinear algorithm method to deal with the downhole project signals. Wang et al. [3]-[4] used a correlation filtering method to deal with the noise of downhole engineering signals. Shaw et al. [5]-[8] proposed a new time domain signal decomposition method using an empirical mode decomposition (EMD) method, which could effectively remove signal interference. Tu et al. [9]-[10] raised a new method based

on Manchester coding to analysis downhole signal noise. Zheng [11] designed a digital filter to optimize downhole signal de-noising. On the basis of EEMD algorithm, Li et al. [12] proposed an adaptive index optimization EEMD algorithm (AIO-EEMD) for signal de-noising.

Although the methods from the above researchers can effectively reduce signal interference, the specificity of downhole interference has not been studied, which may eliminate the original characteristics of the signal [13]-[15]. The downhole engineering signal has many peaks and abrupt parts, which is its particularity. Wavelet analysis can effectively distinguish abrupt parts and noise in the signal, and detect transient components in the signal. So it can detect weak signals and enhance signal-to-noise ratio, so as to realize the de-noising of non-stationary signals [16]-[18]. A few researchers have used wavelets to deal with the downhole data. Giaouris et al. [19]-[20] developed a wavelet-denoising approach for downhole signals using nonlinear wavelet transform threshold value. Kim Kyong-il et al. [21] proposed an improved wavelet threshold function for acoustic signal de-noising based on wavelet transform.All of these methods can distinguish the sharp peak and abrupt change in the underground engineering signal from the noise to a certain extent and realize the effective de-noising of the underground signal.

However, the traditional wavelet threshold function will cause data oscillation and deviation when processing data, this paper proposes a method based on the combination of feedback wavelet transform and improved wavelet threshold function to de-noise downhole engineering signals. In view of the limitations of the traditional single de-noising effect evaluation index, a comprehensive evaluation index is proposed as the evaluation parameter of the signal de-noising effect to determine the best wavelet decomposition scale and the optimal wavelet basis.The experiment shows that the improved method has a remarkable effect on the de-noising of downhole data, which provides good support for obtaining accurate data in drilling engineering.

II. Downhole Engineering Parameter Signal and Noise Characteristic Analysis

Downhole engineering parameters include pressure, temperature, drilling pressure, torque, acceleration and bending stress. All of these parameters are collected and transmitted through downhole engineering instruments. In order to investigate engineering parameters de–noising approach, it is very important to analyze the noise characteristics of down-hole data [22]-[24]. Noise in Drilling Well Sites is an important factor that affects the regular work of instruments, which reduces the SNR (Signal-to-Noise Ratio) of the received signal. The sources of the noise in downhole engineering can be divided into three aspects. The first aspect is the man-made noise caused by human activities, such as diesel engines, generators, mud pumps, drilling rigs and other equipment. The second aspect is natural noise, such as all kinds of

electromagnetic wave sources in nature. The third aspect is the instrument internal noise generated by the system itself, such as the white noise of semiconductor components, the $1/f$ noise caused by circuit board wiring, and the internal power noise of the instrument [23]. The approximate spectrum distribution and the frequency range of these internal and external noises are shown in Fig. 1.
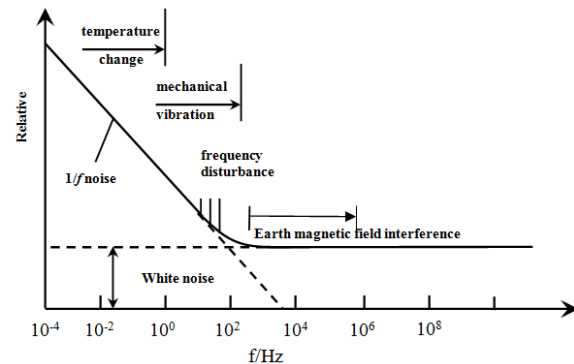

Fig.1 Noise Distribution

In the received engineering signals, there are various random noises, of which white Gaussian noise (WGN) accounts for the most. In the signal processing, the mean variance of a wavelet transform of white noise will decrease with the increment of decomposition number. So white noise has negative singularity. However, for the original signal, the modulus maximum of its wavelet transform increases with the increment of decomposition layers [26]-[27]. Wavelet de-noising method distinguishes signals and noises by changing the trend of different modulus maxima in multiscale space. Therefore, the number of the wavelet decomposition has a major impact on the de-noising effect. Wavelet transforms that are characterized by multi-resolution analysis can extract weak signals and meet the need of processing LWD data in harsh environments.

III. Model for Downhole Engineering Signal De-noising

A. Feedback basic principle of wavelet de-noising method

Signals of downhole instruments are mainly interfered by WGN, so this paper mainly studies wavelet de-noising for WGN [28]. The basic principle of wavelet threshold de-noising is as follows.

Assuming that a finite length signal superimposed with WGN can be expressed as:

$$s(i) = f(i) + \sigma e(i), (i = 1, 2 \cdots, n-1) \quad (1)$$

Where, $f(i)$ is the true signal, $e(i)$ is a standard white noise, and σ is the noise level. Using the wavelet threshold method, the accurate signal $f(i)$ can be recovered from the noisy signal $s(i)$. The algorithm is shown in Fig. 2.
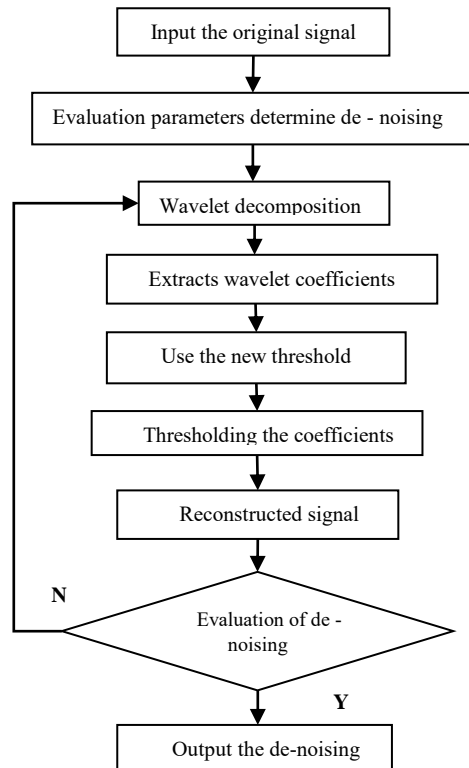
Fig.2 Wavelet threshold de-noising algorithm

(1) The wavelet transform of a noisy signal is carried out, and the appropriate wavelet basis and wavelet decomposition level j is selected to decompose the noisy signal to the j layer, and the corresponding wavelet decomposition coefficient $w_{j,k}$ can be obtained.

(2) Threshold quantization of high frequency coefficient of wavelet decomposition: according to a threshold quantization criterion, the high frequency coefficient of each layer from the first layer to the j layer is processed by determining the appropriate threshold function to obtain the estimated value of the wavelet coefficient $w_{j,k}^{*}$.

(3) Wavelet reconstruction: the wavelet inverse transformation is carried out for the high-frequency wavelet coefficients of layer 1 to layer j and the low-frequency wavelet coefficients of layer j after quantized by threshold value, to obtain the estimated signal, so as to recover and obtain the useful signal.

(4) The evaluation parameters are used to check the de-noising effect of the signal. The de-noising effect of different decomposition scales and different wavelet bases are compared, then return to step (1) according to the difference of the de-noising effect.

The feedback wavelet threshold de-noising algorithm takes the multi index fusion as the evaluation parameter of the de-noising effect, and the multiple indexes include the root mean square error, signal to noise ratio, smoothness and so on. After de-noising using the wavelet threshold, the de-noised signal is evaluated and feedback is carried out according to the evaluation parameters.

B. Improved wavelet de-noising threshold function

According to the characteristic analysis of downhole engineering parameters, the downhole engineering data was abrupt and intensive [29]. An improved threshold function is proposed. This method can overcome the shortcomings of a traditional threshold function that can cause oscillation and deviation, and it can effectively de-noise engineering parameters. There are two major traditional threshold operators:

(1) Hard thresholding,

$$w_{j,k}^{*} = \begin{cases} w_{j,k}, & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases} \tag{2}$$

The disadvantage of this method is that at some point it will generate a break, and the reconstructed signal will produce oscillation.

(2) Soft thresholding,

$$w_{j,k}^{*} = \begin{cases} \mathrm{sgn}(w_{j,k}) \cdot (|w_{j,k}| - \lambda), & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases} \tag{3}$$

Although the overall continuity of soft thresholding is better than hard thresholding, when $|w_{j,k}| \geq \lambda$, there is always a constant deviation between $w_{j,k}$ and $w_{j,k}^{*}$, which directly affects the degree of approximation of the signal after the de-noising and the accuracy of the signal, and affects the de-noising effect of the signal. The above two threshold operators have been widely used in engineering problems, but there are some limitations in practical applications. In order to overcome the different defects of the soft-threshold operators and hard-threshold operators, an improved threshold operator is constructed.

$$w_{j,k}^{*} = \begin{cases} \mathrm{sgn}(w_{j,k}) \cdot \left| |w_{j,k}| - \dfrac{2\lambda}{1 + e^{((|w_{j,k}| - \lambda)/2)}} \right|, & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases} \tag{4}$$

The improved threshold operators, like the soft threshold operators, is a continuous function, which can overcome oscillation caused by the hard threshold de-noising method.

$$f(w_{j,k}) = \mathrm{sgn}(w_{j,k}) \cdot \left| |w_{j,k}| - \frac{2\lambda}{1 + e^{((|w_{j,k}| - \lambda)/2)}} \right|,$$

When $w_{j,k} > 0, f(w_{j,k}) = w_{j,k} - \dfrac{2\lambda}{1 + e^{((|w_{j,k}| - \lambda)/2)}}, w_{j,k} \to +\infty$,

$$\frac{f(w_{j,k})}{w_{j,k}} \to 1 - \frac{2\lambda}{1 + e^{((|w_{j,k}| - \lambda)/2)}} \cdot \frac{1}{w_{j,k}} \to 1;$$

When $w_{j,k} < 0, f(w_{j,k}) = w_{j,k} - \dfrac{2\lambda}{1 + e^{((|w_{j,k}| - \lambda)/2)}}, w_{j,k} \to -\infty$,

$$\frac{f(w_{j,k})}{w_{j,k}} \to 1 + \frac{2\lambda}{1+e^{\left(\left(|w_{j,k}|-\lambda\right)/2\right)}} \cdot \frac{1}{w_{j,k}} \to 1 ;$$

$$f(w_{j,k}) - w_{j,k} = \text{sgn}(w_{j,k}) \cdot \frac{2\lambda}{1+e^{\left(\left(|w_{j,k}|-\lambda\right)/2\right)}}, w_{j,k} \to \pm\infty ,$$

$$f(w_{j,k}) - w_{j,k} \to 0 .$$

The asymptote of the improved threshold function is $f(w_{j,k}) = w_{j,k}$, which overcomes the constant deviation caused by the soft threshold de-noising method.

In addition to the selection of the threshold function, the other important aspect is the specific estimation of the threshold λ [30]. In this paper, a number of experiments have been carried out to obtain the threshold, which is $\lambda = \sigma\sqrt{2\lg(M)} / \log(j+1)$, here M is the length of signal and j is the decomposition level. The expression of the noise standard deviation $\sigma = median(w_{j,k}) / 0.6745$.

C. Wavelet de-noising effect comprehensive evaluation

The evaluation indexes of common signal de-noising are root mean square error (RMSE), signal to noise ratio (SNR) and smoothness (R) [31]-[32].

(1)RMSE:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[f(i) - f^{\wedge}(i)\right]^2} \tag{5}$$

Where, $f(i)$ is the original signal, $f^{\wedge}(i)$ is the de-noised signal, and n is the length of the signal. Eq. (5) shows that the smaller the RMSE, the better the signal de-noising effect.

(2)SNR:

$$SNR = 10\log_{10}\left(power_{signal} / power_{noise}\right) \tag{6}$$

Where,

$$power_{signal} = \frac{1}{n}\sum_{i=1}^{n}\left[f(i)\right]^2 \tag{7}$$

$$power_{noise} = \frac{1}{n}\sum_{i=1}^{n}\left[f(i) - f^{\wedge}(i)\right]^2 = RMSE^2 \tag{8}$$

Eq. (6) illustrates that the higher the SNR, the better the signal de-noising effect.

(3)R:

$$R = \sum_{i=1}^{n-1}\left[f^{\wedge}(i+1) - f^{\wedge}(i)\right]^2 / \sum_{i=1}^{n-1}\left[f(i+1) - f(i)\right]^2 \tag{9}$$

Eq. (9) shows that the smaller the smoothness, the better the signal de-noising effect.

According to the characteristics of the above RMSE, SNR and R, the fusion index F can be weighted by the entropy method. The fusion index F is obtained as an evaluation parameter for the de-noising effect. Its specific formula is

$$F = W_{RMSE} \cdot C_{RMSE}(m) + W_{SNR} \cdot C_{SNR}(m) + W_R \cdot C_R(m) \tag{10}$$

Where, W_{RMSE} is the weight coefficient of RMSE, W_{SNR} is the weight coefficient of SNR, W_R is the weight coefficient of R.

$$C_{RMSE}(m) = \frac{VRM(m) - \min(RMSE)}{\max(RMSE) - \min(RMSE)} \tag{11}$$

$$C_{SNR}(m) = \frac{VSNR(m) - \min(SNR)}{\max(SNR) - \min(SNR)} \tag{12}$$

$$C_R(m) = \frac{VR(m) - \min(R)}{\max(R) - \min(R)} \tag{13}$$

$C_{RMSE}(m), C_{SNR}(m)$ and $C_R(m)$ denote the normalized value of the RMSE variation, the SNR variation and the R variation respectively.

Where,

$$VRM(m) = RMSE(m+1) - RMSE(m) \tag{14}$$

Eq.14 shows that VRM(m) indicates that RMSE(m) is the change in the wavelet decomposition scale between the m+1 and the m level; RMSE (m) indicates the root mean square error at the M decomposition level.

$$VSNR(m) = SNR(m+1) - SNR(m) \tag{15}$$

In the same way, VSNR (m) represents the change of SNR between level m+1 and level M, SNR (m) means the signal-to-noise ratio at the M decomposition level.

$$VR(m) = R(m+1) - R(m) \tag{16}$$

VR (m) means the variation of R between level m+1 and level m, R (m) indicates the smoothness of the M decomposition scale. Further, taking VRM (m) as an example, the calculation method of the weight coefficient is given,

$$W_{RMSE} = \frac{1 - H_{RMSE}}{(1 - H_{RMSE}) + (1 - H_{SNR}) + (1 - H_R)} \tag{17}$$

$$H_{RMSE} = -\left(\frac{1}{\ln(n)}\right)\sum_{i=1}^{n}P_i^{RMSE}\ln P_i^{RMSE} \tag{18}$$

Where, H_{RMSE} represents index entropy and n represents sequence length.

$$P_i^{RMSE} = \frac{RMSE(i)}{\sum_{i=1}^{n}RMSE(i)} \tag{19}$$

Here, P_i^{RMSE} represents probability.

The weight coefficients of SNR and R can be calculated in the same way.

IV. OPTIMUM WAVELET DECOMPOSITION LEVEL AND BEST WAVELET BASIS

The improved wavelet threshold function was used to de-noise, with combining root mean square error (RMSE), signal-to-noise ratio (SNR), smoothness (R) and fusion indexs

(F), The de-noising effects of different decomposition scales and different wavelet bases are compared through computer simulation in MATLAB®, so as to determine the optimal scale and wavelet base of underground engineering parameters decomposition. Fig. 3 shows the comparison of the changes of RMSE, SNR, R and F under different wavelet decomposition scales.
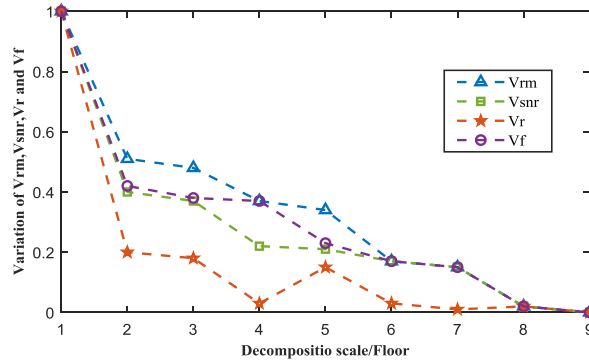

Fig.3 Variation of the Vrm、Vsnr、Vr and Vf

The MATLAB Function Block was applied to simulate the non-stationary and random signals, with 2048 sampling points and the SNR being 2dB in each signal. It can be seen from Fig. 3, the changes in root mean square error, signal-to-noise ratio, smoothness and fusion index all show obvious convergence characteristics along with the increase of decomposition scale, and these index values all tend to flatten out when the decomposition scale is greater than 5. Therefore, it can be concluded that the optimal scale of wavelet decomposition of the improved wavelet threshold function is 5.White noises are superimposed on the Blocks signals to obtain the noisy signals, with the SNR being approximately 15 dB (Fig. 4a). The noisy signal is de-noised with the haar, the Sym8 and the db3, as demonstrated in Figs. 4(b)-(d), which indicates that the signal obtained by Haar wavelet de-noising is the smoothest, the curve obtained is closer to the original signal, and the reconstructed signal can better reflect the details of the original signal.Therefore, Haar is chosen as the wavelet basis in this study.
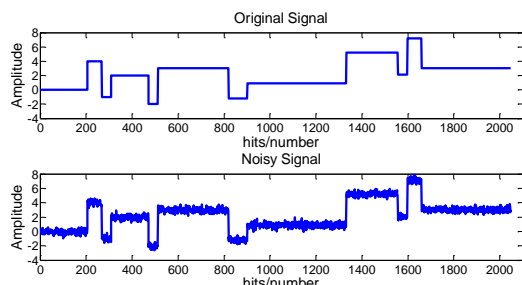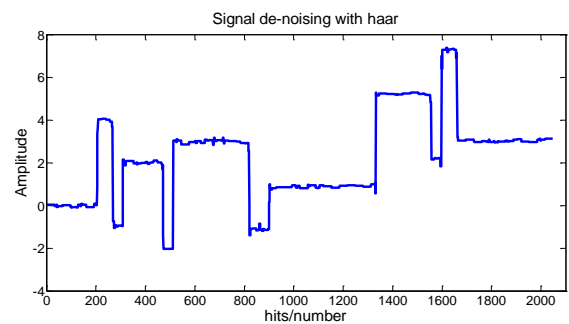

Original signal and noisy signal
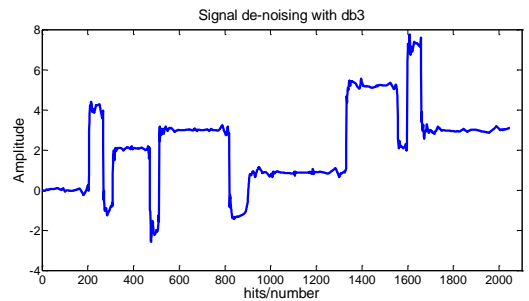
Signal de-noising with db3
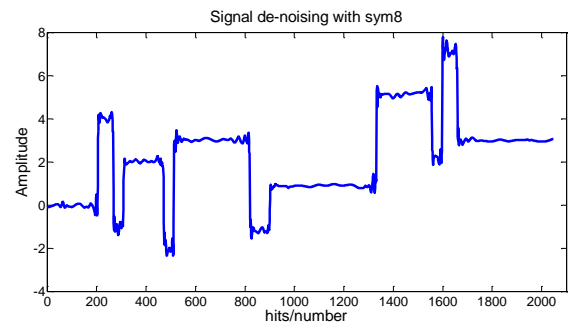
Signal de-noising with sym8

Signal de-noising with haar

Fig.4 db3、sym8 and haar at level 5 de-noising signals

V. RESULTS AND DISCUSSION

A. Downhole Engineering Measured Parameters Processing and Analysis

The improved threshold de-noising method is used to de-noise the measured drilling pressure and torque signal of the downhole. Drilling pressure data from the Wen Xing 5th well is shown in Fig. 5a. The drilling pressure signal de-noised by the improved threshold function is shown in Fig. 5b.
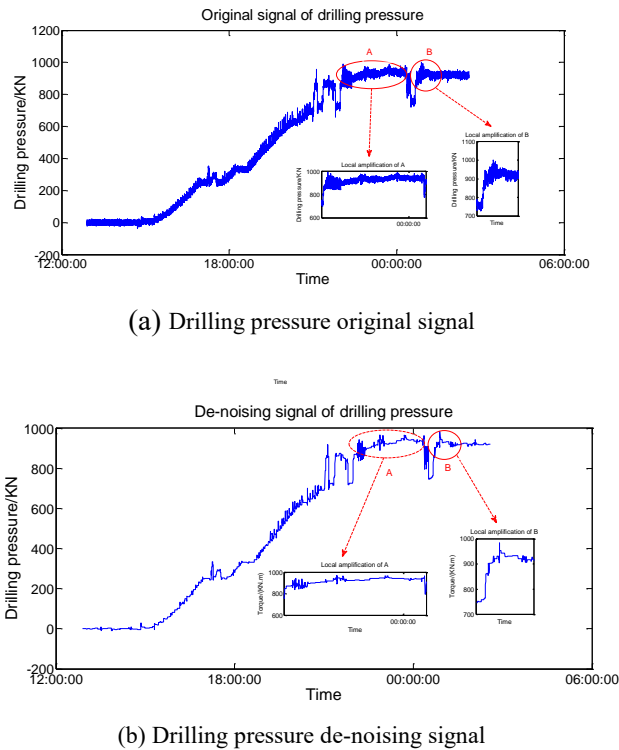
(a) Drilling pressure original signal

(b) Drilling pressure de-noising signal

Fig.5 Experimental results of Drilling pressure de-noising signal

Table 1 RMSE, SNR, R and F comparison

Experimental Index	Hard-threshold	Soft-threshold	improved threshold
Rmse	5.5015	5.0023	4.7823
Snr	35.0079	36.2759	38.5871
R	0.2390	0.2362	0.1419
F	8.7884	7.1130	6.8176

According to the parameters of RMSE, SNR, R and F in Table 1, it can be seen that for downhole drilling pressure signal de-noising, the root mean square RMSE, smoothness R and comprehensive evaluation index F of the improved threshold function de-noising are smaller than the traditional threshold function, And its signal-to-noise ratio SNR is higher than the traditional threshold function, indicating that the de-noising effect of the improved threshold function is better than that of the soft and hard threshold function.By comparing the region A in Figs. 5(a) and (b), it can be seen that in the stage of relatively stable drilling pressure change, the improved threshold wavelet de-noising makes the drilling pressure data clearer. By comparing the region B in Figs. 5(a) and (b),it can be seen that in the stage when the torque changes dramatically, This method can effectively suppress the white noise and sharp pulse interference in the drilling pressure signal, retain the original characteristics of the original signal, and reflect the actual drilling pressure value more accurately. Drilling pressure data is an important parameter affecting rock drillability [34]. After wavelet de-noising, the drilling pressure data can accurately reflect the actual downhole drilling pressure value, which is good for engineers to understand and analyze the downhole conditions.
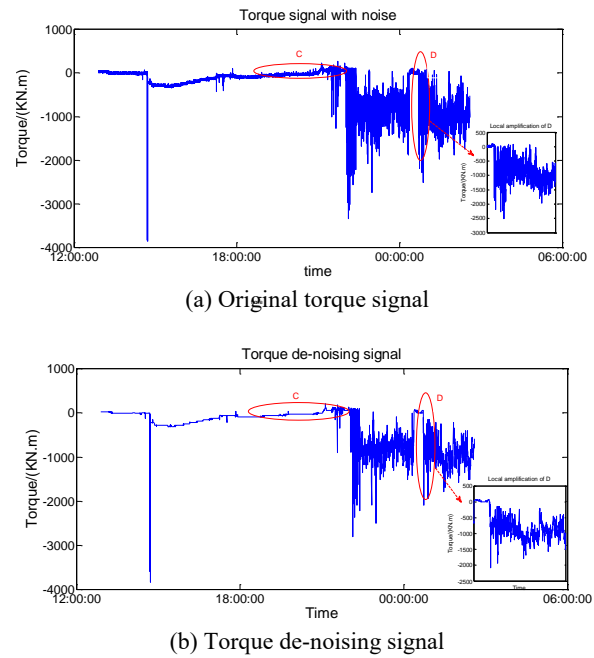

(a) Original torque signal

(b) Torque de-noising signal

Fig.6 Experimental results of Torque de-noising signal

Table 2 RMSE, SNR, R, and F comparison

Experimental Index	Hard-threshold	Soft-threshold	improved threshold
Rmse	8.0365	7.0332	6.4728
Snr	27.6256	29.5623	31.7088
R	2.351	1.3570	0.9993
F	10.9782	9.2265	8.7474

The measured original torque signal is shown in Fig. 6a. The de-noised torque signal is shown in Fig. 6b. Table 2 shows that the de-noising effect of the improved threshold function is improved compared with the soft and hard threshold function. Fig. 6 illustrates that most of the noise is effectively suppressed, and the reconstructed signal basically preserves the full details of the original signal. By comparing the region C in Figs. 6(a) and (b), it can be seen that in the stage of relatively stable torque change, the improved threshold wavelet de-noising can effectively filter out the " glitches" generated by white noise and obtain a relatively smooth reconstructed signal, which enables engineers to grasp the torque change more accurately. By comparing the region D in Figs. 6(a) and (b), it can be seen that in the stage when the torque changes dramatically, the improved threshold function wavelet de-noising can effectively suppress the white noise and sharp pulse interference in the torque signal. This method preserves the mutation position of the useful signal under the condition of strong noise, and thus preserves the original characteristics of the torque signal.Torque is an important basis for judging downhole drilling tool operation conditions, bit wear conditions and underlying lithology [35]. It is the most vital parameter for judging the underlying lithology and drillability. The torque after de-noising can accurately calculate its relative variation, thus providing a reliable basis for engineers.

VI. CONCLUSION

In this paper, by analyzing the signal characteristics of the downhole engineering parameters, a new threshold function of wavelet de-noising approach was determined for LWD signals. Through theoretical analysis and experimental verification, the following conclusions can be obtained:

1) Compared to traditional downhole engineering signal processing methods, the proposed method can overcome the disadvantage of constant deviation between estimation wavelet coefficient and decomposition wavelet coefficient, aiming at the disadvantage of data oscillation and deviation caused by traditional threshold function wavelet transform in downhole data processing.

2) Concerning the limitation of traditional single evaluation index of de-noising effect, a comprehensive evaluation index is proposed as the evaluation parameter of de-noising effect. In the Blocks Matlab simulation experiment, the optimal wavelet de-noising scale is 5 based on the convergence characteristics of the change in root mean square error, signal-to-noise ratio, smoothness and fusion index F. By comparing the de-noising effects of different wavelet bases at the decomposition scale of 5, the optimal wavelet basis is Haar wavelet.

3) An improved threshold function based wavelet denoising method for underground engineering parameters is proposed in this paper.The experimental results show that the method can effectively suppress the white noise and sharp pulse interference in the downhole WOB and torque signals, retain the characteristics of the original signal such as sharp peak and sudden change, and more accurately reflect the actual information in the downhole, thus providing a reliable measuring method for the analysis of the working state of the bit.

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