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RESEARCH ON SHAFT DEFORMATION IDENTIFICATION BASED ON MULTI-SENSOR DATA FUSION OF HOISTING CONVEYANCE

To validate the feasibility of SDI using HCOC and lay a theoretical foundation for SD monitoring, the SDI research is conducted based on HCOC. Firstly, a noise reduction algorithm for the AITQWPT is proposed based on the TQWT, the high-frequency components above a certain decomposition level are iteratively processed by a filter bank and finely decomposed. The particle swarm optimization algorithm is employed to automatically optimize quality factor parameters, and its fitness function is constructed based on kurtosis and correlation coefficients, which can perform frequency band selection and reconstruction and achieve noise reduction of HCOC under SD. Its denoising performance is evaluated through simulation models and test bench data. Secondly, on the basis of AITQWPT and residual convolutional neural network, a multi-sensor data fusion model for SDI is constructed according to the HCOC under SD. The normalized data from AITQWPT after denoising is input into the residual convolutional neural network, where the convolutional layer extracts shallow features, the pooling layer achieves dimensionality reduction, and the concatenation layer finishes the feature-level fusion. The fused features sequentially pass through residual modules for deep feature extraction, then input into the fully connected layer, and the SDI is performed through SoftMax function and the effectiveness is verified. The analysis results indicate that the proposed denoising method can effectively suppresses the interference components, highlight the SD characteristics, and has strong robustness for HCOC under SD. The multi-sensor data fusion model achieves the complementarity of SD feature, reduces the number of layers and complexity of residual convolutional networks, verifies the feasibility of SDI through HCOC, and enhances the SDI accuracy. The aforementioned research revolutionizes the paradigm of SD monitoring, provides scientific guidance for SDI through HCOC and theoretical support for accelerating its industrial application.

Keywords: Shaft deformation; hoisting conveyance; operating characteristics; data fusion; identification

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1. Introduction

The vertical shaft, serving as the lifeline of coal mining operations, directly determines the coal production safety. Influenced by factors such as the coal seam occurrence, overlying rock properties, mining methods, and improper preservation of protective pillars, coal seam extraction can cause displacement and deformation of the overlying strata, which in turn leads to shaft deformation (SD) [1]. The SD exacerbates the instability of hoisting conveyance (HC) through contact with guide roller and rail, and leads to accidents such as HC jamming or failing [3-5]. A typical mine hoisting system is illustrated in Fig. 1. According to incomplete statistics, over a hundred shafts in mining areas such as Huainan, Xuzhou, and Jining in China have suffered varying degrees of damage. The losses at the Haizi Mine exceeded three million dollars. At the Shimen Iron Mine, a HC fell into the shaft, resulting in the deaths of 13 people. Therefore, it is essential to monitor SD in real time and promptly implement countermeasures to ensure the mining operation safety.

Current monitoring methods for SD primarily include GPS, concrete strain gauge, pressure cell, fiber optic grating, inertial measurement unit, and 3D laser scanning technology. Wang et al. [6] employed GPS to monitor the ground deformation around shaft and processed the monitoring data with Kalman filtering, and demonstrated through field experiments that this method can detect minute dynamic deformations. Bruneau et al. [7] installed monitoring equipment including glass slides, displacement sensors, and guide rail connection plates to better understand the failure mechanism of shafts and monitor its deformation state. Tao et al. [8] monitored the shaft lining in the bedrock section during construction, thawing, and the post-thawing period by deploying four fiber optic sensors in the testing layer, and obtained the variation patterns of vertical and circumferential strains. Piao et al. [9] installed fiber optic grating sensors in the overburden layer to monitor vertical and circumferential deformation of surrounding topsoil around shaft. Lyu et al. [10] used resistive linear displacement sensors to monitor both longitudinal and radial displacements at the aquifer-aquitard interface, the bottom aquifer-bedrock interface, and the upper section of the horsehead. Yan et al. [11] employed a non-contact full-field strain measurement system and resistive strain gauges to monitor a SD experimental model. Wang et al. [12] arranged four concrete strain measurement points along the reinforcement mesh on the inner surface of shaft lining, and each point was equipped with vertical and tangential concrete strain gauges to monitor its strain variation patterns. The aforementioned deformation monitoring methods have a limited number of measurement points and damage the shaft structure and its replacement and repair are quite difficult when it malfunctioning, and it can only monitor deformation in partial or easily damaged sections of the shaft. Walton et al. [13] identified deformation mechanisms by scanning surface features of tunnel and shaft lining using lidar, and enhanced the precision of contour analysis through elliptical fitting algorithms. Tarasov et al. [14] put forward a new technique of real-time measurement of displacement on inner surface of concrete lining by laser scanning, and the results are presented as the estimates of the change in the shaft diameter, circumferential strains and ellipticity. Zhu et al. [15] developed a multi-sensor fusion system for monitoring shaft lining deformation using a 2D lidar, IMU, and stepper motors, which can significantly reduce measurement time and simplify the measurement process. Gu et al. [16] proposed a novel method for real-time 3D model reconstruction, deformation detection, and accessibility analysis of rescue shafts using an RGB-D camera, it can capture depth and color data from the shaft's low-texture walls. The method imposes stringent environmental requirements on shaft such as light and dust, and the complex shaft equipment is installed on the shaft lining, which obstructs laser beam transmission. Therefore, the novel monitoring methods for SD should be explored.

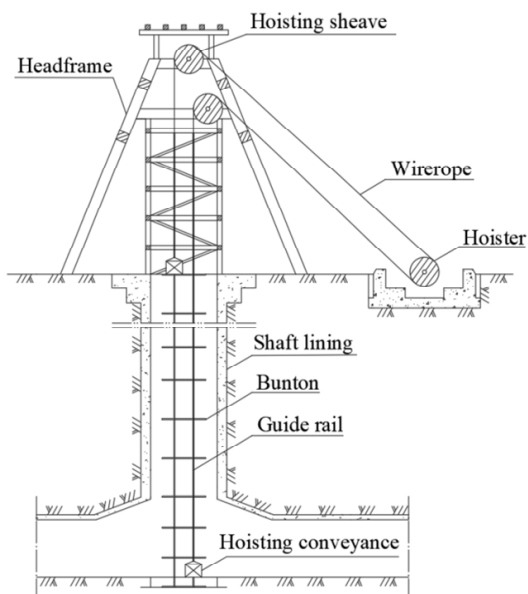


Fig. 1. Mine hoisting system

SD not only exacerbates the HC instability but also endows it with rich deformation characteristics. Its data acquisition equipment is simple to install and covers the entire shaft. The subtle fault features associated with SD can be revealed through in-depth analysis, and the shaft distortion risks can be identified. Wan et al. [17] constructed feature vectors by extracting energy characteristics and time-domain indicators from elevator car vibration signals using optimal wavelet packet analysis, and employed a least-squares support vector machine to diagnosis elevator fault. Ma et al. [18] extracted maximum and average values from the vibration and tilt angle signals of HC as input parameters for decision tree, and identified the inclination, local bulging, and misalignment fault. Wu et al. [19] calculated the dynamic regularization distance between the test and selected sample for HC vibration signal, and completed the fault identification of guide rail. Jia et al. [20] employed singular value decomposition and wavelet transform to preprocess elevator car vibration signals and extracted wavelet energy features, and these features were then input into a one-dimensional convolutional neural network to achieve operational state recognition. Niu et al. [21] constructed a fault tree for elevator systems based on expert knowledge and multi-source data, and achieved an optimal fault diagnosis sequence for elevator vibration faults through dynamic attribute-based ideal solution similarity ranking optimization. The aforementioned analysis of hoisting conveyance operational characteristics (HCOC) implements identification of its motion state and guide rail faults. However, it overlooks the SD features inherent in operational characteristics. There is an urgent need to construct a shaft deformation identification (SDI) model based on HCOC, suppress interference components from dynamic properties, and enhance the in-depth mining and fusion analysis of multi-source data.

Aiming to SDI research through HCOC, a noise reduction algorithm of an adaptive incomplete tunable quality factor wavelet packet transform (AITQWPT) is proposed based on the tunable quality factor wavelet transform (TQWT), which can enhance frequency resolution in the

high-frequency. It employs a particle swarm optimization algorithm for automatic optimization of quality factor and evaluates its denoising performance using simulation models and conveyance operational data from experimental apparatus. A multi-sensor data fusion model for SDI is constructed based on HCOC. The convolutional layer extracts shallow-level features, which are then reduced in dimension via the pooling layer. Features from each shallow layer undergo feature-level fusion through a concatenation layer. The fused features sequentially pass through residual modules for deep-level feature extraction, and achieve feature-level integration of sensor data. The fully connected layer is inputted into the SoftMax function to realize SDI. This establishes a new paradigm for SDI, and provides theoretical support to accelerate its industrial application.

2. Denoising algorithm of HCOC based on AITQWPT

The TQWT can select an appropriate quality factor based on the analyzed signal characteristics. It is easily adjustable, possesses perfect reconstruction and moderate over completeness properties, and is fully discrete [22,23]. When the decomposition level falls below a certain threshold, the high-frequency range becomes relatively broad, and requires refined decomposition. Drawing on the principles of wavelet packet transform, dual-channel filter banks and scaling are iteratively applied to the high-frequency components, forming an incomplete tunable quality factor wavelet packet transform. Concurrently, an optimization algorithm is employed to find optimal quality factor and decomposition level, constituting an AITQWPT.

2.1. Tunable quality factor wavelet transform

The TQWT is achieved by iteratively applying dual-channel filter banks and scaling on its low-pass channel. Its three-layer decomposition and reconstruction structure are shown in Fig. 2. Where f_s is the input signal sampling frequency, α_e is the low-pass scaling (LPS) factor, β_e is the

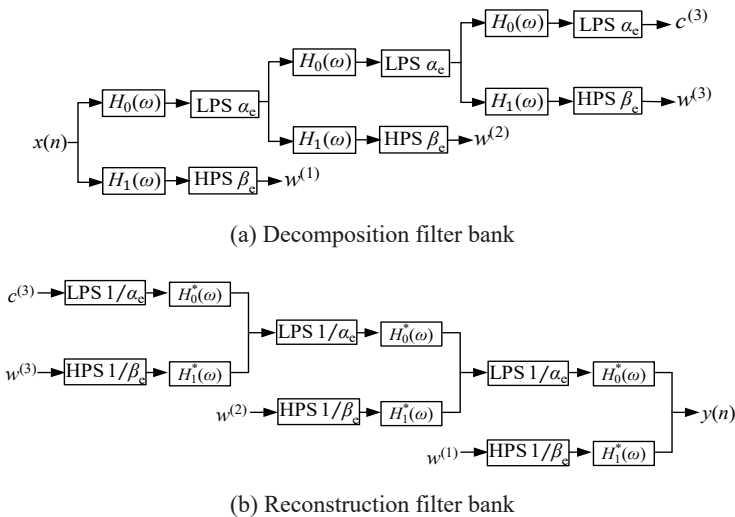


Fig. 2. Decomposition and reconstruction of TQWT

high-pass scaling (HPS) factor, the decomposition level is J_e and $j \leq J_e$, and $c^{(j)}$ and $w^{(j)}$ represent the high-frequency and low-frequency sub-band signals obtained from the j th-order filter bank. The sampling frequency are $\alpha_e^j f_s$ and $\beta_e \alpha_e^{j-1} f_s$ respectively, $c^{(j)}$ is the input to the $(j+1)$ -order filter bank, and $H_0(\omega)$ and $H_1(\omega)$ represent the low-pass and high-pass filter response functions. H_0^* and H_1^* are the complex conjugates of $H_0(\omega)$ and $H_1(\omega)$ [24].

To ensure that the TQWT possesses perfect reconstruction properties and avoids excessive redundancy, the scaling factor must satisfy Eq. (1). Due to the transition bands in $H_0(\omega)$ and $H_1(\omega)$, these transition bands should be constructed using Eq. (2), with the specific expressions for $H_0(\omega)$ and $H_1(\omega)$ shown in Eqs. (3) and (4).

$$0 < \alpha_e < 1, \quad 0 < \beta_e \leq 1, \quad \alpha_e + \beta_e > 1 \quad (1)$$

$$\begin{cases} \theta^2(\omega) + \theta^2(\pi - \omega) = 1 \\ \theta(\omega) = 0.5 \times (1 + \cos \omega) \times \sqrt{2 - \cos \omega} \end{cases} \quad |\omega| \leq \pi \quad (2)$$

$$H_0(\omega) = \begin{cases} 1, & |\omega| \leq (1 - \beta_e)\pi \\ \theta\left(\frac{\omega + (\beta_e - 1)\pi}{\alpha_e + \beta_e - 1}\right), & (1 - \beta_e)\pi < |\omega| < \alpha_e\pi \\ 0, & \alpha_e\pi \leq |\omega| \leq \pi \end{cases} \quad (3)$$

$$H_1(\omega) = \begin{cases} 0, & |\omega| \leq (1 - \beta_e)\pi \\ \theta\left(\frac{\alpha_e\pi - \omega}{\alpha_e + \beta_e - 1}\right), & (1 - \beta_e)\pi < |\omega| < \alpha_e\pi \\ 1, & \alpha_e\pi \leq |\omega| \leq \pi \end{cases} \quad (4)$$

As the decomposition layers changes, the filter center frequency f_z and bandwidth BW vary, and its calculation formula is shown in Eq. (5). The scale factors α_e and β_e , quality factor Q_e , and redundancy factor r_e are related as shown in Eq. (6). The maximum decomposition layers $J_{\max}$ can be obtained via Eq. (7) for different (Q_e, r_e) .

$$f_z = \alpha_e^j \frac{2 - \beta_e}{4\alpha_e} f_s, \quad BW = \frac{1}{2} \beta_e \alpha_e^{j-1} f_s \quad (5)$$

$$\beta_e = \frac{2}{Q_e + 1}, \quad \alpha_e = 1 - \frac{\beta_e}{r_e} \quad (6)$$

$$J_{\max} = \left\lceil \frac{\log(\beta_e N / 8)}{\log(1/\alpha_e)} \right\rceil = \left\lceil \frac{\log[N / (4(Q_e + 1))]}{\log[(Q_e + 1) / (Q_e + 1 - 2/r_e)]} \right\rceil \quad (7)$$

Where N is the signal length.

To directly obtain decomposition results under different levels, the decomposition of multi-level filters and scaling should be made equivalent, as shown in Fig. 3. Fig. 3(a) shows

the equivalent of approximate part, and Fig. 3(b) shows the detail part, as shown in Eqs. (8) and (9). By performing operations of input signal with $H_0^{(j)}(\omega)$ and $H_1^{(j)}(\omega)$ at a given level, the decomposition result of specific level can be obtained.

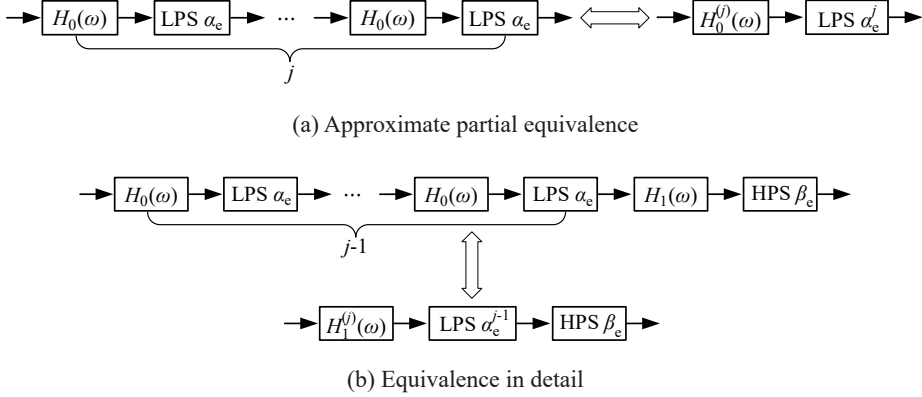


Fig. 3. Equivalence of multistage filters and scaling

$$H_0^{(j)}(\omega) = \begin{cases} \prod_{m=0}^{j-1} H_0(\omega/\alpha_e^m), & |\omega| \leq \alpha_e^j \pi \\ 0, & \alpha_e^j \pi < |\omega| \leq \pi \end{cases} \quad (8)$$

$$H_1^{(j)}(\omega) = \begin{cases} H_1(\omega/\alpha_e^{j-1}) \prod_{m=0}^{j-2} H_0(\omega/\alpha_e^m), & (1-\beta_e) \alpha_e^{j-1} \pi \leq |\omega| \leq \alpha_e^{j-1} \pi \\ 0, & |\omega| < (1-\beta_e) \alpha_e^{j-1} \pi \text{ } \blacklozenge \text{ } \alpha_e^{j-1} \pi < |\omega| \leq \pi \end{cases} \quad (9)$$

2.2. Incomplete tunable quality factor wavelet packet transform

Given α_e , β_e and J_e , the frequency domain of $H_1^{(j)}(\omega)$ in the TQWT can be expressed as $((1-\beta_e)\alpha_e^{j-1}\pi, \alpha_e^{j-1}\pi)$ corresponding to $w^{(j)}$, as shown in Fig. 4. As the decomposition levels increases, its frequency resolution continuously improves and exhibits adaptability [25][26]. Although the interval ranges for the same j but different α_e and β_e vary, the range becomes relatively large when j is below a certain threshold. To achieve refined decomposition of the high-frequency components, dual-channel filter banks and scaling are iteratively applied to the high-frequency components based on the wavelet packet transformation. For the high-frequency components above a certain decomposition level, the aforementioned process is repeated, and its level J_p is determined by Eq. (10). The detail coefficients from 1 to $J_p - 1$ level are iteratively processed using the filter banks until J_p level. This constitutes an incomplete tunable quality factor wavelet packet transform, as shown in Fig. 5, where $J_p = 3$ and $J_e = 4$.

$$J_p = \log_{\alpha_e}(0.2/\beta_e) + 1 \quad (10)$$

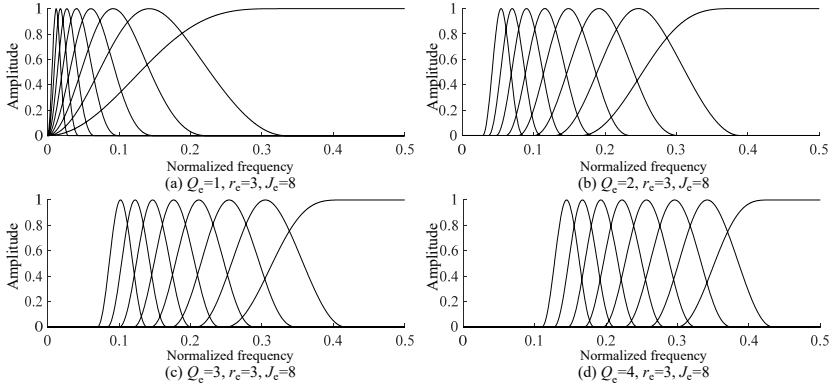


Fig. 4. Frequency range corresponding to $H_1^j(\omega)$ given Q_e , r_e and J_e

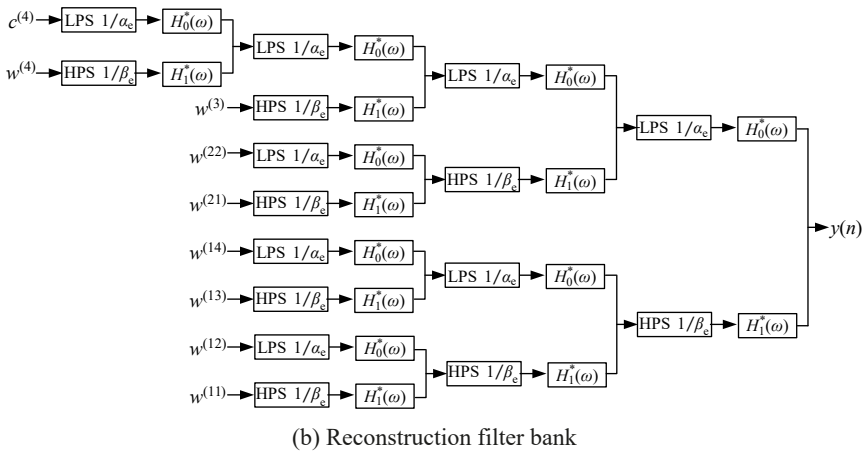
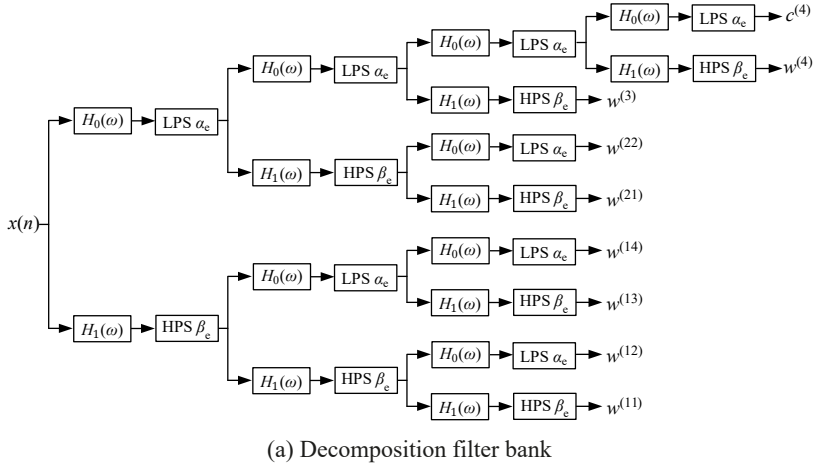


Fig. 5. Decomposition and reconstruction of ITQWPT

2.3. Adaptively incomplete tunable quality factor wavelet packet transform

The signal undergoes an incomplete tunable quality factor wavelet packet transform, and its individual branches are reconstructed. The correlation coefficients and kurtosis of each reconstructed signal are calculated using Eqs. (11) and (12), respectively. The frequency band is selected and reconstructed for its correlation coefficients exceeding a given threshold τ and kurtosis coefficients below a given threshold γ . This process filters out certain interference components, and achieves noise reduction for the original signal. However, the denoising effect is significantly influenced by the parameters Q_e and Q_c , and its manual parameter settings are difficult to adapt to the analyzed signal characteristics, which can lead to suboptimal denoising results. To enhance denoising performance, an AITQWPT is developed by optimizing parameter Q_e using a particle swarm optimization algorithm, and the decomposition level Q_c is set to the maximum decomposition level $J_{\max}$. The fitness function of the particle swarm optimization algorithm is established by combining the correlation coefficient and kurtosis of each reconstructed signal as shown in Eq. (13), and the parameter iteration formula is shown in Eq. (13) to (17). The parameters are set as follows: $m_c = 50$, $t_{\max} = 100$, $v_{\min} = -1$, $v_{\max} = 1$, $x_{\min} = 1$, $x_{\max} = 30$, $\tau = 0.2$, $\gamma = 3$. To quantitatively analyze the denoising performance, evaluation metrics such as SNR and RMSE are introduced, as shown in Eq. (18) and (19).

$$r_k = \frac{\sum_{i=1}^N (\mathbf{x}(i) - \bar{\mathbf{x}})(\mathbf{y}_k(i) - \bar{\mathbf{y}}_k)}{\sqrt{\sum_{i=1}^N (\mathbf{x}(i) - \bar{\mathbf{x}})^2} \sqrt{\sum_{i=1}^N (\mathbf{y}_k(i) - \bar{\mathbf{y}}_k)^2}} \quad k = 1, 2, 3, \dots, M-1, M \quad (11)$$

$$Ku_k = \frac{1}{N} \sum_{i=1}^N \left(\frac{(\mathbf{y}_k(i) - \bar{\mathbf{y}}_k)}{\sigma} \right)^4 \quad k = 1, 2, 3, \dots, M-1, M \quad (12)$$

$$P = \sum_{k=1}^M \left(r_k + \frac{Ku_k}{10} \right) \quad k \text{ satisfies } r_k \geq \tau \text{ and } Ku_k \leq \gamma \quad (13)$$

Where $\mathbf{x}$ is the original signal, $\bar{\mathbf{x}}$ is the mean of $\mathbf{x}$, $\mathbf{y}_k$ is the k -th single-branch reconstructed signal, $\bar{\mathbf{y}}_k$ is the mean of $\mathbf{y}_k$, M is the number of reconstructed signals, k is the decomposed frequency band, r_k is the correlation coefficient between the k -th single-branch reconstructed signal and the original signal, Ku_k is the kurtosis of the k -th single-branch reconstructed signal, P is the particle fitness, and τ and γ is the corresponding thresholds.

$$v_i^{k_c+1} = wv_i^{k_c} + c_1 \times r_a \times (p_i - x_i^{k_c}) + c_2 \times r_b \times (p_g - x_i^{k_c}) \quad (14)$$

$$w = \max w - k_c \times \frac{\max w - \min w}{\max k} \quad (15)$$

$$c_1 = b_1 + \frac{b_2 \times k_c}{t_{\max}}, \quad c_2 = b_3 + \frac{b_4 \times k_c}{t_{\max}} \quad (16)$$

$$x_i^{k_c+1} = x_i^{k_c} + v_i^{k_c+1} \quad (17)$$

Where w is the inertia weight, k_c is the current iteration count, i is the i -th particle, $v_i^{k_c}$ is the particle velocity, $x_i^{k_c}$ is the particle position, p_i is the individual extreme value, p_g is the global extreme value, c_1 and c_2 are learning rates, r_a and r_b are random numbers between (0, 1), $\max w$ is the maximum inertial weight, typically set to 0.9, $\min w$ is the minimum inertial weight, typically set to 0.4, $t_{\max}$ is the maximum iteration count, and $0 < b_1 + b_2 \leq 2$, $b_3 - b_4 \geq 1$, typically set as a $b_1 = 1$, $b_2 = 0.5$, $b_3 = 6$, and $b_4 = 2$.

$$SNR = 10 \lg \left(\frac{\sum_{i=1}^N x_c^2(i)}{\sum_{i=1}^N (x_c(i) - x_q(i))^2} \right) \quad (18)$$

$$RMSE = \sqrt{\sum_{i=1}^N (x_c(i) - x_q(i))^2 / N} \quad (19)$$

Where x_c is the signal without noise, and x_q is the denoised signal.

2.4. Denoising algorithm validation of adaptive incomplete tunable quality factor wavelet packet transform

To demonstrate the effectiveness and reliability of the proposed denoising method, the AITQWPT is applied to reduce noise on HCOC of both the dynamic simulation model and experimental apparatus. The simulation data originates from [27], and its dynamic model is shown in Fig. 6. The hoisting acceleration is 0.18 m/s^2 for a duration (0, 14) s, it then operates at a con-

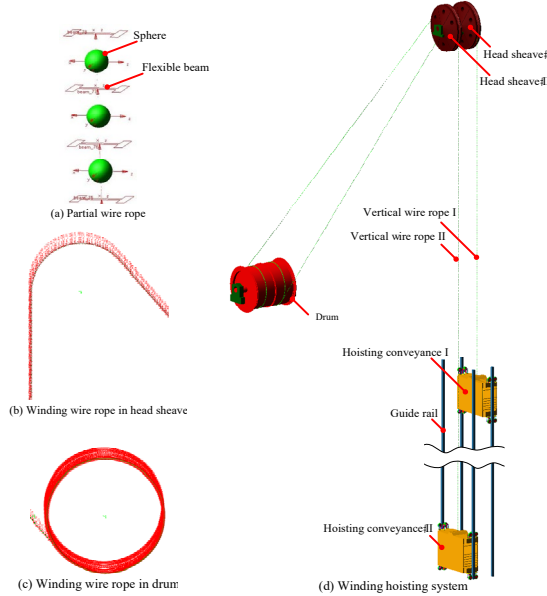


Fig. 6. Dynamic simulation model of mine winding hoisting system

stant speed for (14, 99) s, and finally decelerates over the period for (99, 113) s. The specific calculation process and parameters have been detailed in [27]. Background noise is simulated by adding Gaussian white noise with signal-to-noise ratios (SNR) of 0, -5, and -15 dB. Due to space limitations of the paper, the denoising evaluation of HCOC is restricted to scenarios where the shaft inclination deformation (SID) is 0.2 mm/m, shaft bending deformation (SBD), shaft dislocation deformation (SDD), and shaft horizontal section deformation (SHSD) amplitudes are each 3 mm, and the bottom aquifer water head drops by 10 m under non-mining shaft deformation (NMSD). The experimental data is obtained from the experimental setup shown in Fig. 27, and the specific procedure is described in Section 2.4.2.

2.4.1. Simulation data validation

(1) Noise reduction for HC displacement signals

Fig. 7(a), (c), and (e) show the HC displacement signals with SNR of 0, -5, and -15 dB, respectively, and Fig. 7(b), (d), and (f) show the denoising signals via AITQWPT. The remaining figures in the section follow the same layout as this one. As shown in Fig. 7(a), (c), and (e), the linear displacement features characterizing the SBD are completely obscured with augmenting noise intensity, and its root mean square errors (RMSE) are 27.95, 50.72, and 90.5, respectively, which indicates that the signal exhibits significant deviation from the original signal and contains a substantial amount of interference components. Fig. 7(b), (d), and (f) exhibit substantial local fluctuations with increasing displacement, and the overall trend aligns with the linear displacement corresponding to SBD. Its interference components are filtered out, and the SNR is significantly enhanced to 14.52, 9.57, and 1.61 dB. The RMSE is reduced to 0.19, 0.18, and 0.26 times, and the linear displacement features representing SBD are highlighted in the time domain.

In Fig. 8(a), (c), and (e), the parabolic characteristics gradually become obscured as noise intensity aggravation in SBD zone, and the substantial random fluctuations occur, which RMSE

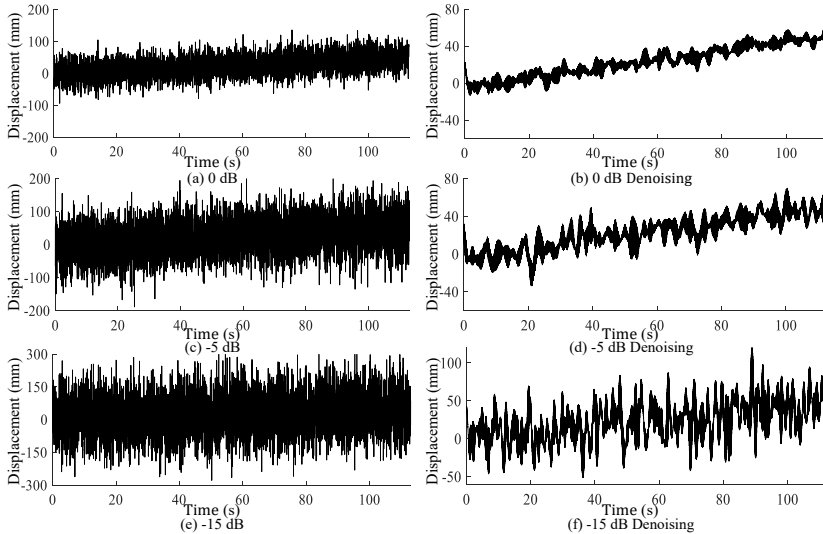


Fig. 7. Denoising of HC displacement signals under SID

are 0.49, 0.88, and 2.83, respectively. After AITQWPT denoising in Fig. 8(b), (d), and (f), the interference components are attenuated, and the SNR are respectively increased to 9.89, 6.22, and -2.17 dB. The RMSE is reduced by 3.3, 3.6, and 4.5 times, and the parabolic characteristics representing SBD are highlighted. In Fig. 9(a), the HC displacement curve exhibits a sawtooth pattern within the area affected by SDD. The sawtooth characteristics are submerged in Fig. 9(c)

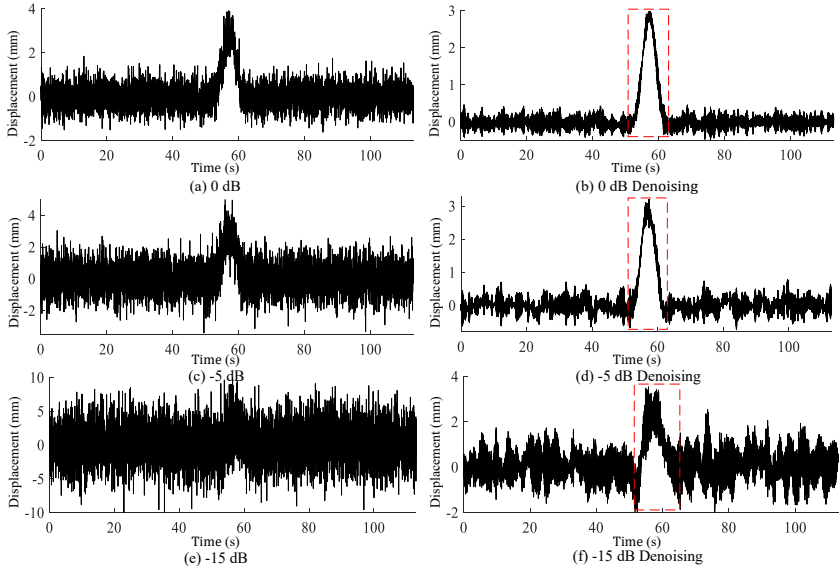


Fig. 8. Denoising of HC displacement signals under SBD

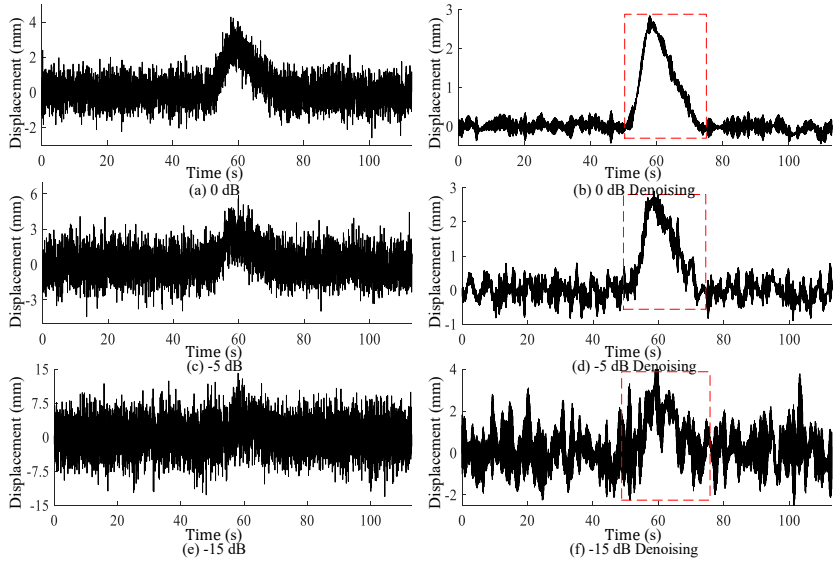


Fig. 9. Denoising of HC displacement signals under SDD

and (e), and the RMSE are 0.66, 1.15, and 3.69. The characteristics in Fig. 9(b) and (d) are fully highlighted with relatively minor local fluctuations, and SNR are 13.75 dB and 6.79 dB, while the RMSE are reduced by 5.1 and 3.8 times. The local fluctuation is intensified in Fig. 9(f), yet the sawtooth characteristics in dislocation zone remains evident in the overall deformation trend. The SNR reaches -2.83 dB, and the RMSE is reduced by 4.1 times. Consequently, the sawtooth feature curve of SBD become more pronounced and reduce noise interference.

As noise intensity aggravation, the rectangular wave features of displacement curves become obscured within the primary deformation zone of SHSD, as shown in Fig. 10(a), (c), and (e). The RMSE are 0.24, 0.42 and 1.39, which are significantly reduced compared with other deformation type. However, the signal still contains a large amount of interference components, primarily due to signal property difference under diverse deformation type. The paper only compares the denoising indicators under same deformation type. Interference components are extensively filtered out in Fig. 10(b), and the rectangular wave features are prominent. In Fig. 10(d), interference components at the wave peaks are amplified, while Fig. 10(f) contains substantial interference components, and the rectangular wave features are covered to a certain extent. Nevertheless, the overall deformation trend still reasonably reflects SHSD characteristics. The SNR are 7.21 dB, 5.03 dB, and -4.43 dB, and the RMSE decreased by 2.4, 3.2, and 3.5 times. The noise interference components are suppressed and the deviation degree from the original signal is reduced.

After denoising by AITQWPT, the low-frequency vibrations are fully highlighted within the primary active zone of NMSD, as shown in Fig. 11(b), (d), and (f). As noise intensity aggravation, the waveform features within active zone remain identical, and only the amplitude is increased. As interference components outside the active region continuously increase, the SNR decreases to 8.92, 8.80, and -3.39 dB. The RMSE are 0.03, 0.03, and 0.15, which are reduced by 3.3, 3.6, and 3.9 times compared to the noise-added signals. The low-frequency fluctuation features within the action zone are less affected by noise intensity, and the denoising method has strong robustness to the low-frequency vibration characteristics of action area.

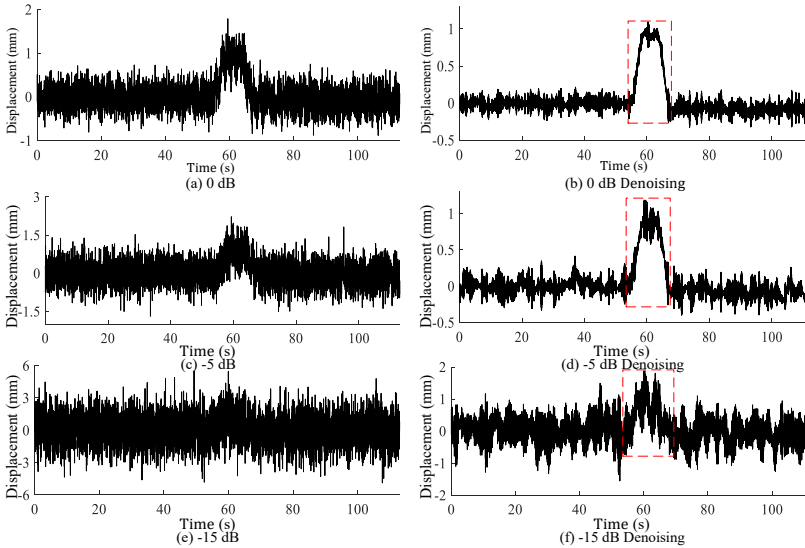


Fig. 10. Denoising of HC displacement signals under SHSD

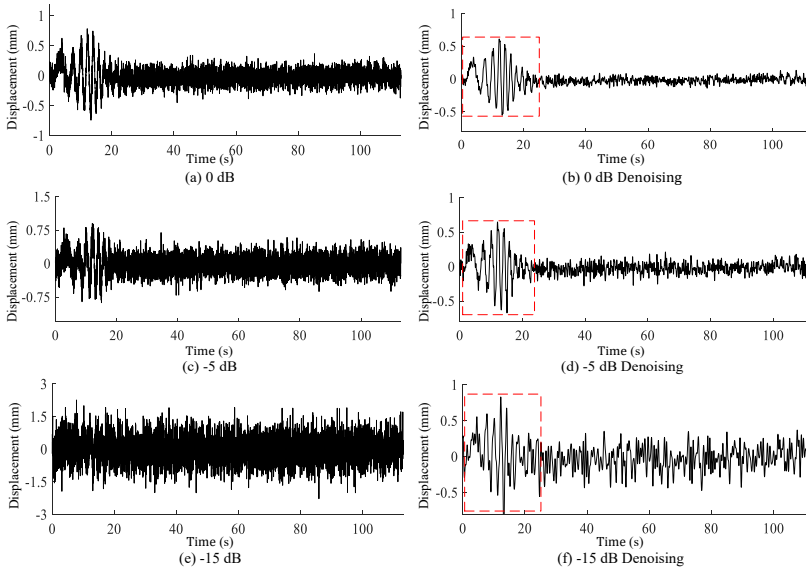


Fig. 11. Denoising of HC displacement signals under NMSD

(2) Noise reduction for HC angular displacement signals

The HC angular displacement signal under SBD contains a large number of interference components after AITQWPT. The interference components in Fig. 12(b), (d), and (f) are intensified, and the overall deformation trend still shows an augmentation of the displacement amplitude

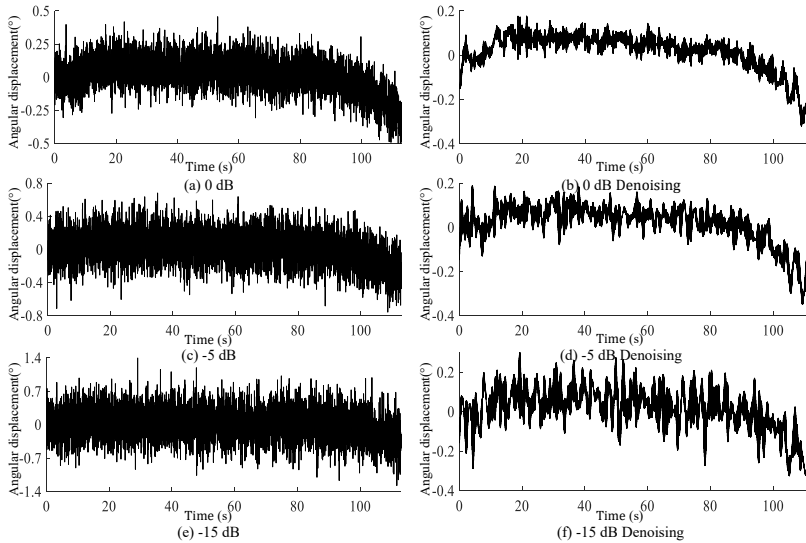


Fig. 12. Denoising of HC angular displacement signals under SID

near the inclination deformation boundary. Then the overall trend decreases, highlighting the SID characteristics. Moreover, the SNR increase to 9.71, 6.85, and 2.15 dB, while the RMSE decrease 3.3, 4, and 3.75 times to 0.003, 0.005, and 0.008, respectively. Noise reduction of the HC angular displacement effectively filters out substantial interference components under SBD, preserves deformation characteristics, and enhances the SNR.

In Fig. 13(a), (c), and (e), the interference components are aggravated at the bidirectional sawtooth features within the SBD zone, and the deviation degree from the original signal aggravates. Its RMSE are 0.004, 0.004, and 0.02. The sawtooth features are basically covered by noise in Fig. 13(e). The features in Fig. 13(b), (d), and (f) are prominent after AITQWPT, and the interference components are suppressed. The SNR increase to 6.28, 4.77, and -2.91 dB, and the RMSE decrease by 2, 3.5, and 4 times, which significantly enhances the ability of HC angular displacement signals to characterize SBD. Similar to SBD, the sawtooth features of angular displacement are submerged as noise intensity aggravation under SBD, as shown in Fig. 14(a), (c), and (e), with RMSE of 0.003, 0.005, and 0.015, respectively. The sawtooth features in Fig. 14(b) and (d) become more prominent, while the interference component amplitude outside this region decreases. The SNR increases to 6.9 and 6.5 dB, and the RMSE is reduced by 2 and 5 times. The interference components are primarily located outside the sawtooth feature area in Fig. 14(f), and the SNR is -2.85 dB and the RMSE is reduced by 3.8 times. A significant amount of SBD features is preserved, enhancing the deformation characterization ability.

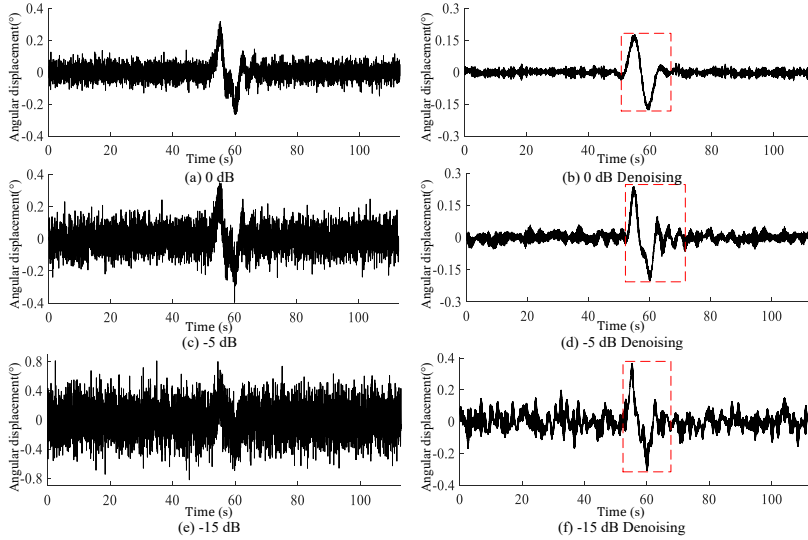


Fig. 13. Denoising of HC angular displacement signals under SBD

The angular displacement on deformation transition zone of SHSD rapidly increases or decreases, and the action area shows reciprocating oscillation with 0° as the equilibrium point. The above features are weakened in Fig. 15(a) and (c), and completely obscured in Fig. 15(e), with RMSE of 0.003, 0.005, and 0.02, respectively. After noise reduction, the reciprocating oscillation characteristics in Fig. 15(b) and (d) are highlighted, with the SNR increasing to 7.61 and

3.57 dB respectively, and the RMSE decreasing by 3 and 2.5 times. Fig. 15(f) exhibits stronger interference components, yet the SNR improves to -2.9 dB, with the RMSE reduced by 5 times. The oscillatory features remain distinctly pronounced compared to Fig. 15(e).

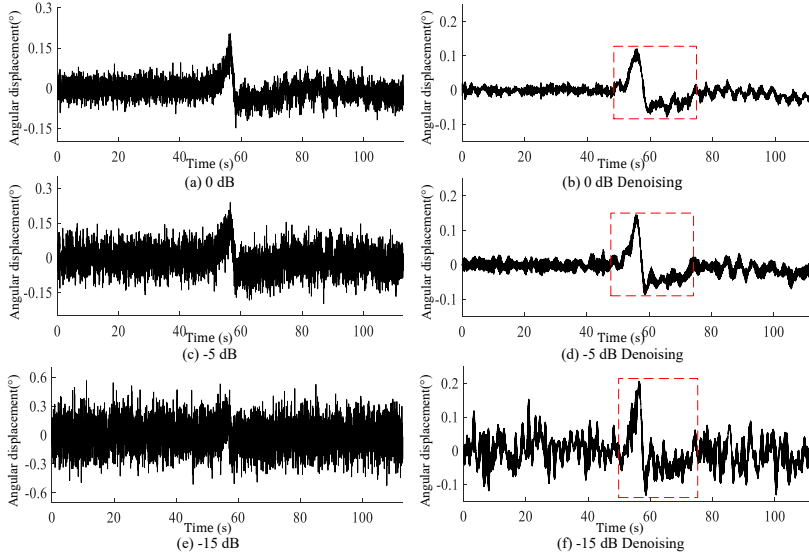


Fig. 14. Denoising of HC angular displacement under SDD

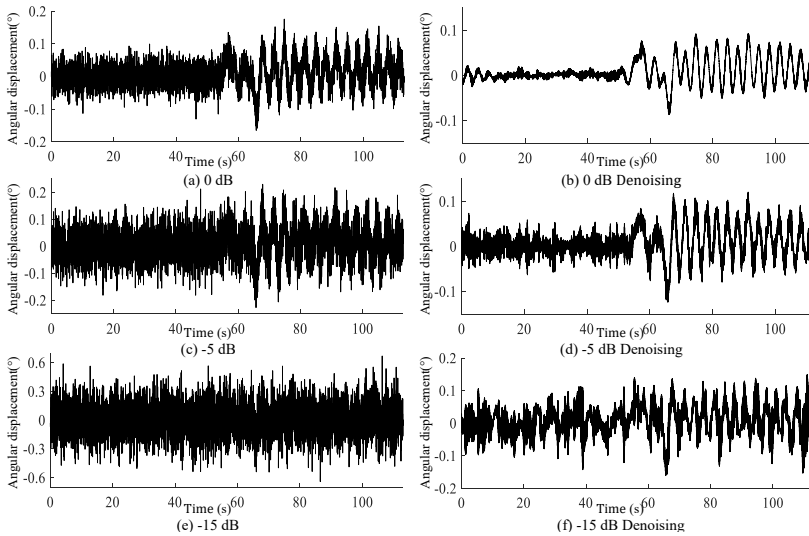


Fig. 15. Denoising of HC angular displacement signal under SHSD

The HC angular displacement signals also exhibit reciprocating oscillation characteristics under NMSD zones, and its period and amplitude undergo changes compare with SHSD.

As noise intensity aggravation, the reciprocating oscillation features become obscured as shown in Fig. 16(a), (c), and (e), and the RMSE are 0.001, 0.002, and 0.0065, respectively. After noise reduction of the HC angular displacement signal in the NMSD zone, its reciprocating oscillations become prominent, as shown in Fig. 16(b), (d), and (f). The SNR increased to 5.04, 2.21, and -3.43 dB, respectively, while the RMSE decreased by 1.6, 2.5, and 3.8 times. The analysis demonstrates that the denoising method effectively suppresses background noise of HC angular displacement signal under strong background noise.

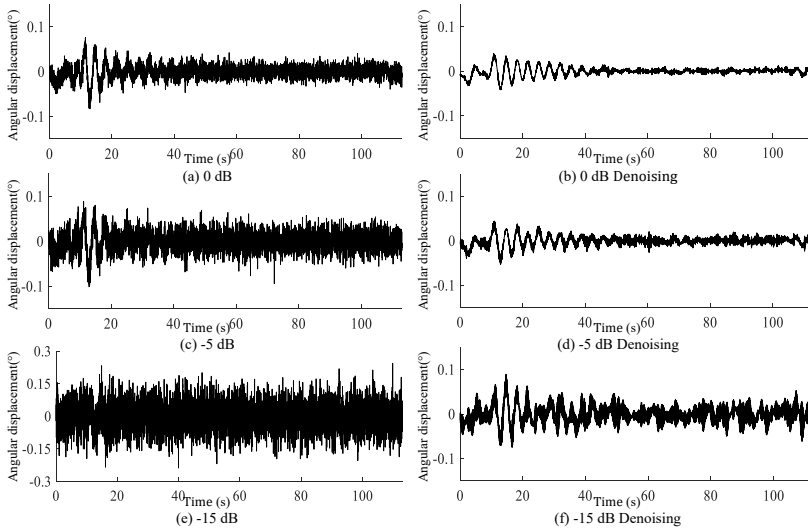


Fig. 16. Denoising of HC angular displacement under NMSD

(3) Noise reduction for HC vibration acceleration signal

The HC vibration acceleration signal exhibits reciprocating oscillation characteristic in SD zone, and its denoising results under different SD types and noise intensities are shown in Fig. 17 to 22. The reciprocating oscillation characteristics representing the SBD are submerged in Fig. 17(a), (c), and (e), and its RMSE are 2.24, 4.06, and 7.06 respectively. A certain degree of reciprocating oscillation component persists at (97, 107) s in Fig. 17(b), (d), and (f), but the prominence of these features is weakened. The SNR are 0.19, -0.69 , and -1.52 dB respectively, and the RMSE decrease to 2.24, 2.47, and 2.72. Although this method exhibits inferior denoising performance for vibration acceleration signal under SID compared to displacement and angular displacement signal, the useful features are still preserved.

The reciprocating oscillation characteristics representing SBD exist abundant interference components and poorer feature prominence around 60 s in Fig. 18(a) and (c). The reciprocating oscillation features are completely obscured, and its RMSE are 1.58, 2.83, and 8.81 dB respectively. After AITQWPT denoising, the SNR in Fig. 18(b), (d), and (f) improves to 2.44, -0.43 , and -4.45 dB, while the RMSE decrease 1.3, 1.7, and 3.3 times. These parameter changes are less pronounced than the prominent degree of reciprocating oscillation, primarily due to strong interference components outside the oscillation region.

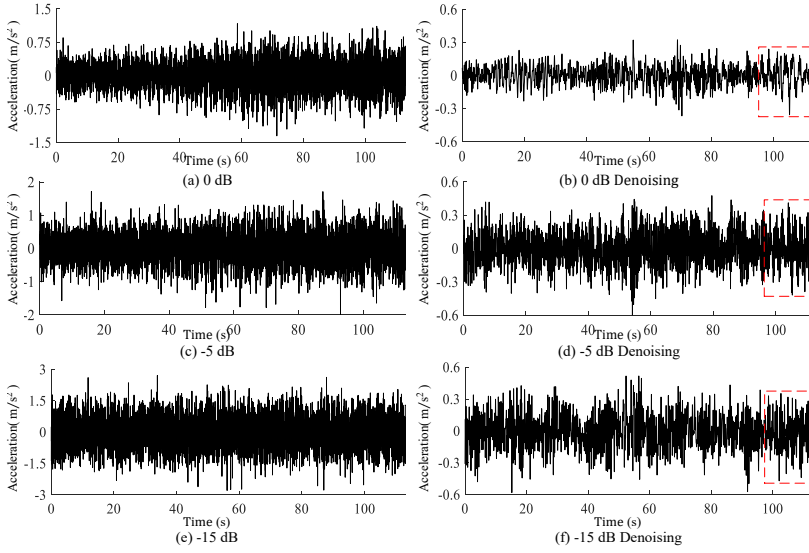


Fig. 17. Denoising of HC vibration acceleration signal under SID

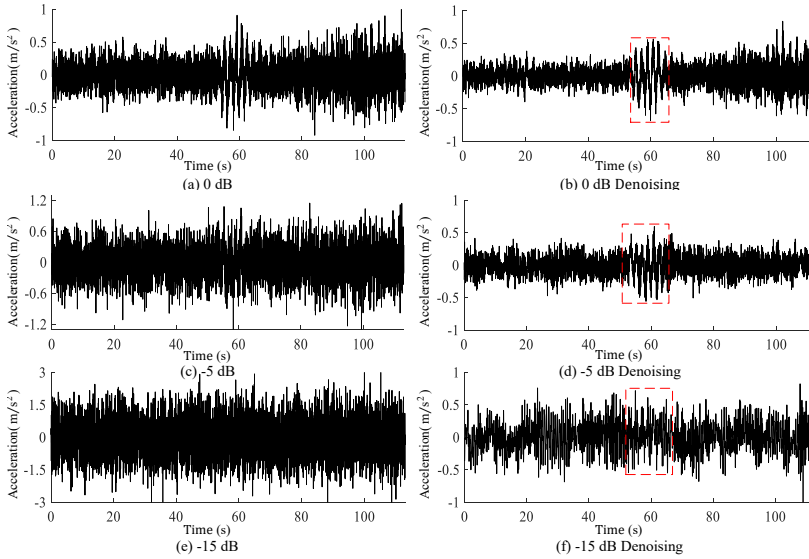


Fig. 18. Denoising of HC vibration acceleration signal under SBD

The reciprocating oscillation characteristics characterizing the SBD in Fig. 19(a), (c), and (e) are weak compared to the bending deformation and are completely submerged, with RMSE of 1.49, 2.65, and 8.36 respectively. After denoising, the characteristics in Fig. 19(b) and (d) are highlighted to a certain extent, but it still contains a large number of interfering components. In Fig. 19(f), the features are still submerged, but its SNR is increased to 2.07, -1.06 and -4.02 dB,

and the RMSE is reduced by 1.3, 1.6 and 3.5 times. The denoising results for the HC angular displacement are shown in Fig. 20 under SHSD. The RMSE for Fig. 20(a), (c), and (e) are 2.21, 3.89, and 12.60, respectively. The reciprocating oscillation characteristic is not completely covered when the SNR is 0 and 5 dB, and fully covered when on -15 dB. After noise reduction, the characteristic is prominent in Fig. 20(b) and (d), and Fig. 20(f) contain substantial interference components and the features are still enhanced to some extent. The SNR improve to 1.68, -0.99 , and -3.88 dB, while the RMSE decrease by 1.2, 1.6, and 3.6 times.

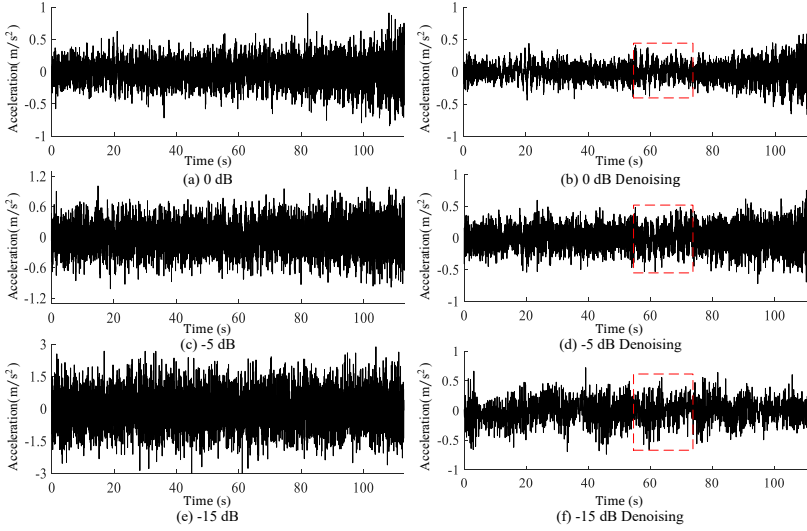


Fig. 19. Denoising of HC vibration acceleration signal under SDD

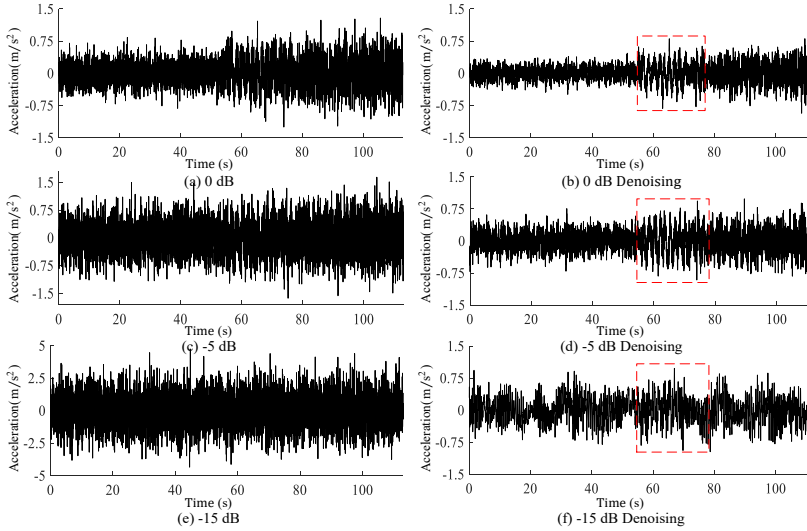


Fig. 20. Denoising of HC vibration acceleration signal under SHSD

In Fig. 21(a), the low-frequency oscillation characterizing NMSD is prominent near 14 s, but the oscillation interval is narrowed. The interference components are enhanced in Fig. 21(c), the oscillation characteristics are covered to a certain extent, and both the oscillation interval and amplitude change. The characteristics are completely submerged in Fig. 21(e), and the RMSE are 1.57, 2.78, and 8.88 respectively. In Fig. 21(b) and (d), the reciprocating oscillation characteristics are prominent, and the interference components are suppressed to a certain extent. The SNR are 2.46 and -1.02 dB respectively. However, there is still strong interference outside the low-frequency oscillation interval, resulting in relatively large RMSE of 1.18 and 1.76 respectively. The low-frequency oscillation interval in Fig. 21(f) contains a large amount of interference components, and the reciprocating oscillation characteristic is enhanced to a certain extent. Compared with Fig. 18(b) and (d), the prominence is relatively poor. The SNR is increased to -4.47 dB, and the RMSE is reduced to 2.63. AITQWPT can still filter out certain interference components of the HC vibration acceleration signal under strong background noise, and highlight the SD feature.

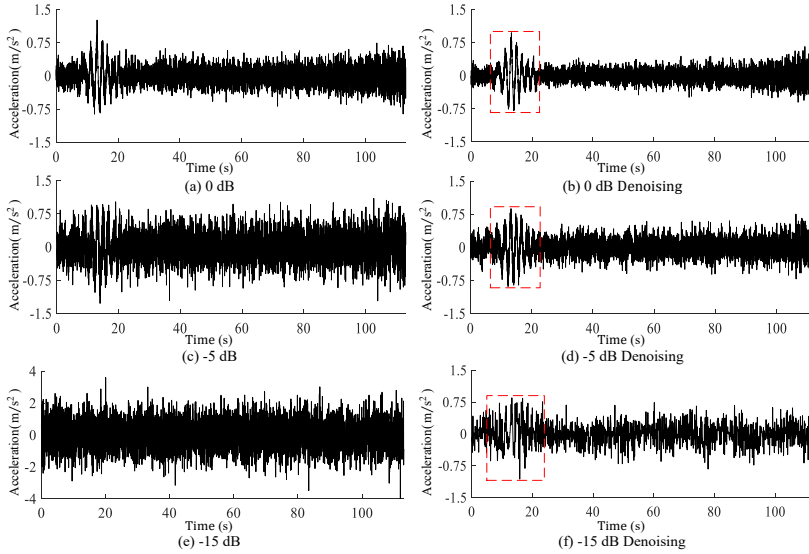


Fig. 21. Denoising of HC vibration acceleration signal under NMSD

(4) Noise reduction for buffer relative displacement signal

The buffer relative displacement signal under SBD is shown in Fig. 22(b), (d), and (f) after noise reduction via AITQWPT. Its compression deformation trend is clearly revealed under diverse noise intensities, and the relative displacement shows a decreasing trend as the HC continues to rise, which is consistent with SBD trend. The local fluctuation interference components intensify with the aggravating noise intensity, the SNR are 9.87, 6.13 and 4.27 dB respectively, and the RMSE are 0.14, 0.22 and 0.27, which are reduced by 3.1, 3.6 and 5.3 times. The SNR is significantly improved, and the signal discretization is reduced. The SBD characteristic is highlighted in the buffer relative displacement signal.

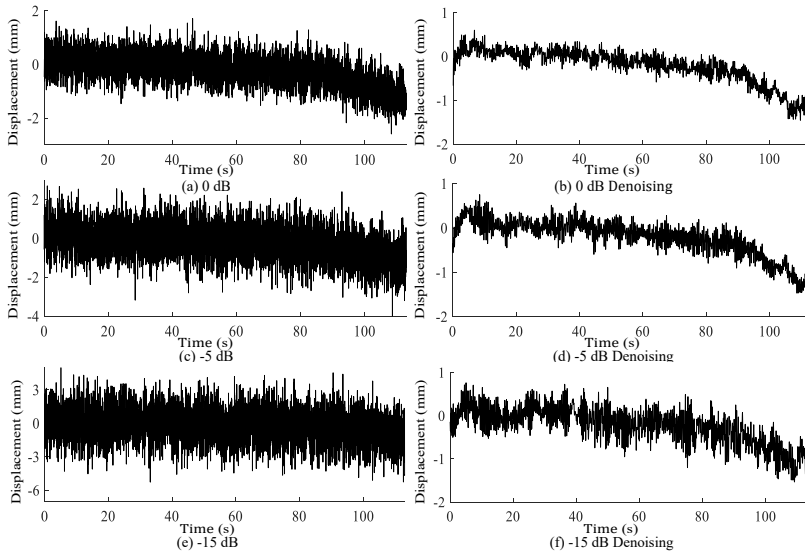


Fig. 22. Denoising of buffer relative displacement signal under SID

Due to the nature of buffer relative displacement signal, the characteristics characterizing SBD are still submerged even though its relatively low SNR as shown in Fig. 23(a), (c), and (e), and its RMSE are 0.20, 0.36, and 1.11, respectively. After noise reduction by AITQWPT, the reciprocating oscillation features near 60 s are prominent in Fig. 23(b) and (d), but they still contain a large amount of interference components. The SNR are 6.08 and 3.34 dB, and the RMSE is

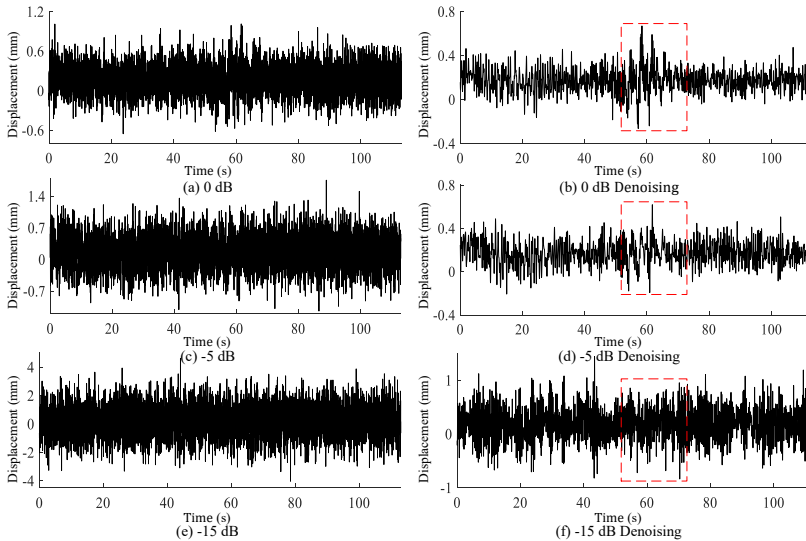


Fig. 23. Denoising of buffer relative displacement signal under SBD

reduced by 2.2 and 2.8 times. Even after noise reduction by AITQWPT under strong background noise, the features are still submerged, as shown in Fig. 23(f). However, the SNR is increased to -3.6 dB, and the RMSE is reduced by 3.7 times. In Fig. 24(b), (d), and (f), the high-intensity interference components exist reciprocating oscillations characterizing the SBD, and the oscillation characteristics are completely submerged. Its SNR are 6.07, 3.39, and -2.36 dB respectively, and the RMSE are 0.09, 0.13, and 0.25, which are reduced by 2.1, 2.6, and 4.4 times. AITQWPT effectively suppresses noise interference in buffer relative displacement signal under SBD and SDD, and highlight feature components. As the noise intensity aggravation, the prominence of time-domain features decreases, but it can still filter out a large number of interference components, improve the SNR, and reduce the signal dispersion.

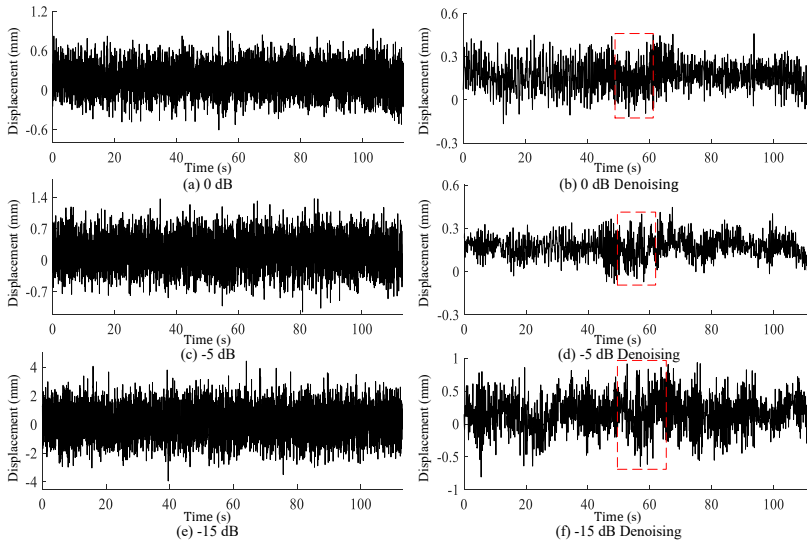


Fig. 24. Denoising of buffer relative displacement signal under SDD

The characteristics representing SHSD are completely obscured under buffer relative displacement, and its RMSE are 0.18, 0.32, and 1.01. After AITQWPT denoising, the low-frequency oscillations near and after 60 s in Fig. 25(b) and (d) become prominent, with SNR of 6.31 and 4.61 dB respectively. The RMSE are reduced by 2.25 and 3.2 times. Both the denoising performance and the prominence of time-domain features are improved. In Fig. 25(f), the enhanced intensity of interference component narrows the low-frequency oscillation interval and significantly reduces its prominence. The SNR reaches -2.54 dB, and the RMSE is reduced by 4.2 times. Although the prominence of time-domain features diminishes, the denoising index relative to the original signal still achieves substantial improvement. The reciprocating oscillatory characteristics representing NMSD are highlighted to a certain extent in Fig. 26(b), (d), and (f). However, as the noise intensity aggravation, the range of the characteristic intervals narrows, and their prominence diminishes. The SNR increases to 5.51, 3.62, and -1.21 dB, and the RMSE decreases to 0.11, 0.13, and 0.23. It has been improved to varying degrees compared with the original signal.

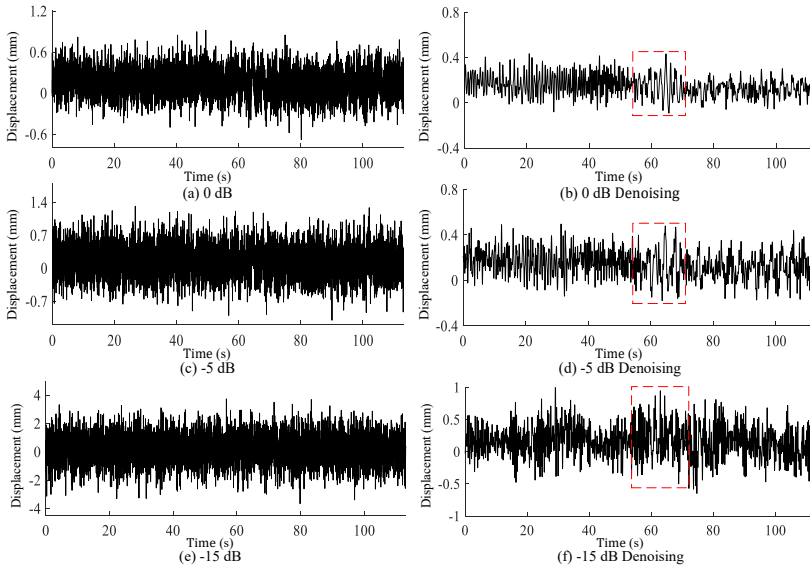


Fig. 25. Denoising of buffer relative displacement signal under SHSD

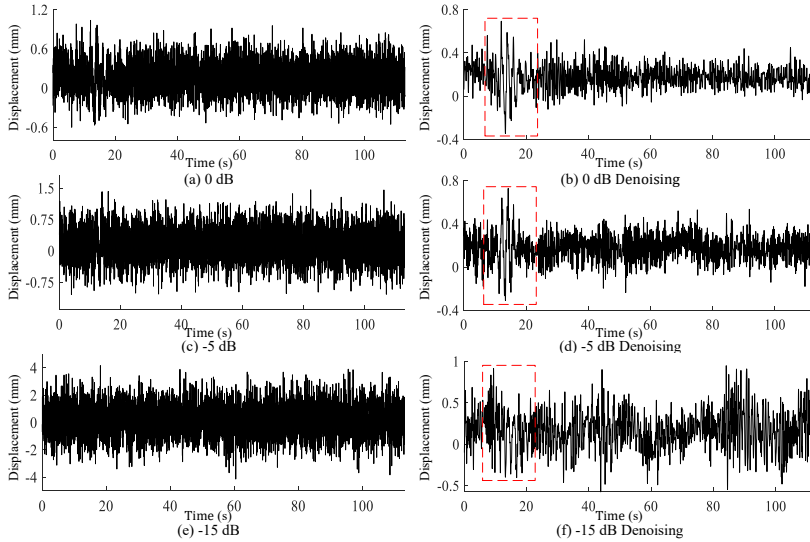


Fig. 26. Denoising of buffer relative displacement signal under NMSD

Through the above analysis, it is found that AITQWPT can suppress the interference components and highlight the SD characteristics under different SD types and noise intensifiers, which indicates that the effectiveness and stability of the proposed denoising method. To further demonstrate the superiority of proposed denoising method, it is compared with methods such as wavelet packet transform, variational modal decomposition, and TQWT, and the results are

shown in TABLE 1. The variational modal decomposition (VMD) has outstanding denoising performance in buffer relative displacement under NMSD, with the SNR improved by 8.3 dB and the RMSE being 0.13. Meanwhile, WPT has relatively excellent denoising performance in the HC vibration acceleration under SBD, and the SNR is increased by 4.18 dB, and the RMSE is 1.73. The proposed method in the paper achieves SNR improvements of 11.85, 4.31, 11.22, 4.57, 13.80, and 8.62 dB, and the RMSE is reduced by several times. It demonstrates outstanding denoising performance across various deformation and signal types, further highlighting its exceptional noise suppression capabilities.

TABLE 1

Evaluation for different noise reduction method

Signal type	Noise reduction method	SNR (dB)	RMSE	Signal type	Noise reduction method	SNR (dB)	RMSE
HC displacement under SID	WPT	0.84	0.009	HC vibration acceleration under SID	WPT	-2.07	2.9
	VMD	2.59	0.007		VMD	-1.43	2.69
	TQWT	4.4	0.006		TQWT	-0.84	2.52
	Proposed method	6.85	0.005		Proposed method	-0.69	2.47
HC displacement under SBD	WPT	2.24	0.38	HC vibration acceleration under SBD	WPT	-0.82	1.73
	VMD	3.98	0.31		VMD	-1.75	1.92
	TQWT	5.53	0.26		TQWT	-1.39	1.84
	Proposed method	6.22	0.24		Proposed method	-0.43	1.65
HC displacement under NMSD	WPT	3.35	0.071	HC vibration acceleration under NMSD	WPT	1.05	0.18
	VMD	5.5	0.056		VMD	3.3	0.13
	TQWT	7.69	0.043		TQWT	2.2	0.15
	Proposed method	8.80	0.03		Proposed method	3.62	0.13

2.4.2. Experimental data validation

Deformed guide rails with varying geometric dimensions and shapes are affixed to the baseline as shown in Fig. 27(f), which can simulate guide rail deformations under SD. Accelerometers CA-DR-3001, inclinometers WT901B, and laser distance sensors PT5070F are installed in Fig. 27(c) and (e) to measure the HC acceleration and angular displacement, and the buffer relative displacement under SD. The acceleration and angular displacement sensors are mounted at the HC upper surface center. A horizontal displacement reference is established as shown in Fig. 27(d), and the laser distance sensor PT5070F measure the distance from the reference to determine HC horizontal displacement. All sensors are connected to the LabJack T4 data acquisition card, which is further linked to the wireless router TL-WR720. The specific technical parameters are detailed in TABLE 2. The HCOC acquisition system developed by LABVIEW is shown in Fig. 27(h), and the system operates within the same local area network as the wireless router TL-WR720, enabling real-time acquisition, display, and storage of HCOC.

Due to the difficulty in manufacturing and installing deformable guide rails, experimental verification is conducted only for partial deformation degrees of diverse SD. The denoising re-



Fig. 27. Experimental station for HCOC under SD

TABLE 2

Technical parameters of measuring device

Type	Name	Value	Type	Name	Value
CA-DR-3001	Measure range (g)	± 1	PT5070F	Detection range (mm)	30~100 mm
	Sensitivity (mV/g)	1000 $\pm$ 10%		Resolution (MBE)	<0.1%
	Frequency response (Hz)	0~800		Precision (MBE)	0.2%
	Operating temperature (°C)	-40~+85		Output mode (mA)	4~20
	—	—		Measuring frequency (kHz)	2.5
WT901B	Measure range (°)	± 90	LabJack T4	Range of simulated input voltage (V)	± 5
	Resolution (°/LSB)	0.0055		Number of analog inputs	12
	Precision (°)	0.2		Resolution (bit)	12
	Output frequency (Hz)	0.2~200		Sampling frequency (K/s)	50

sults are shown in Fig. 28, and the signal sampling frequency is 50 Hz and the sampling duration is 113 s. Fig. 28(a) highlights the overall attenuation trend of angular displacement representing SBD. Fig. 28(b) and (c) emphasize the parabolic and low-frequency oscillation characteristics representing SBD. Fig. 28(d) and (e) reveal the low-frequency oscillation characteristics representing SDD and NMSD. The above results demonstrate that AITQWPT can effectively filter out substantial interference components from actual signal and highlight SD characteristics, which further underscores the superiority and reliability of its denoising performance.

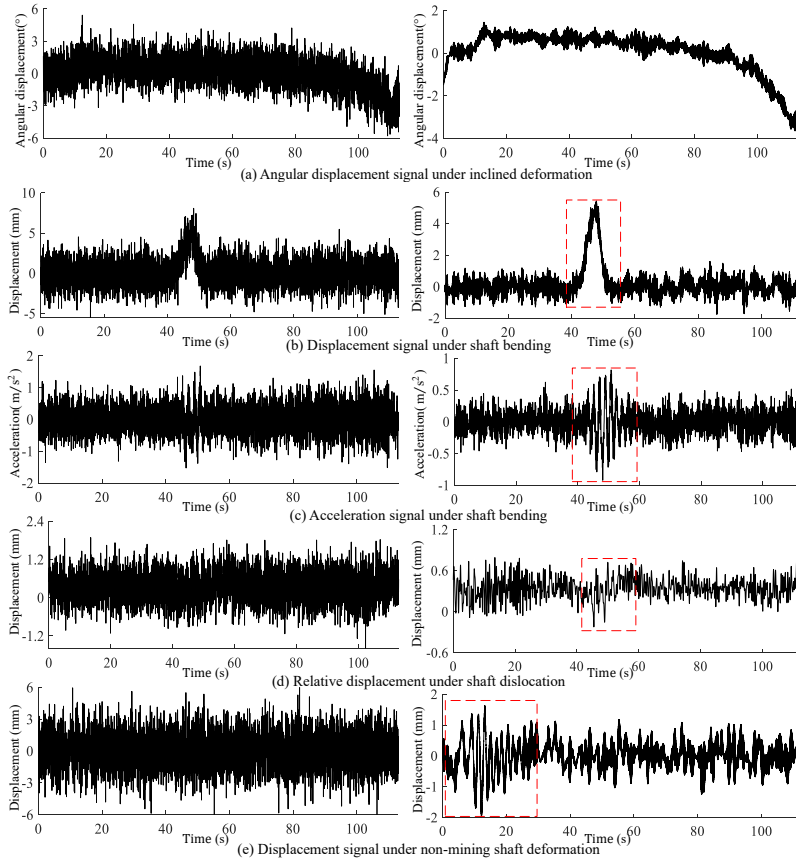


Fig. 28. Denoising of experimental signal

3. Shaft deformation identification model of multi-sensor data fusion

3.1. Theoretical foundations of residual convolutional neural network

As the number of network layer increases, convolutional neural network experiences gradient vanishing or explosion, leading to training difficulty and performance degradation [28]. Residual

convolutional neural networks effectively resolve the degradation issues in deep networks by introducing an identity mapping between inputs and outputs, thereby preventing gradient vanishing and explosion. It primarily consist of convolutional layer, pooling layer, fully connected layer, and residual module [29][30].

3.1.1. Convolutional layer

Convolution layer extracts feature information through multiple distinct convolution kernels, and the kernel is continuously slid to capture local features at different positions, while its weight remains constant throughout the sliding process. The computation process of a one-dimensional convolutional layer is illustrated in Fig. 29. The $1 \times m_c$ convolution kernel slides along the $1 \times n_c$ input signal x with a stride of d_c to perform the convolution operation, and the result is then added to the bias constant b_c . The input data undergoes a nonlinear mapping via the ReLU defined by Eq. (21), the output result is shown in Eq. (20), and the output feature Y has a scale of $1 \times c_c$.

$$y_{1,i} = f \left(\sum_{j=1}^{m_c} w_{1,j} \cdot x_{1,(i-1) \cdot d_c + j} + b_c \right) \quad (20)$$

$$f(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases} \quad (21)$$

Where $y_{1,i}$ is the nonlinear mapping of the convolution kernel with the local signal $(x_{(i-1) \cdot d_c}, \dots, x_{(i-1) \cdot d_c + m_c})$, w_{1,m_c} is the kernel weight values, and $f(x)$ is the ReLU.

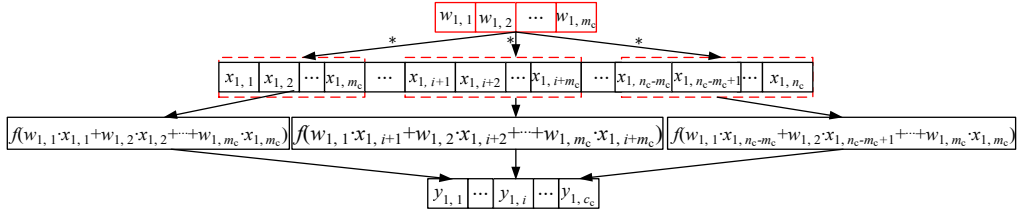


Fig. 29. One-dimensional convolutional layer computation

3.1.2. Pooling layer

Pooling layer typically follows single or multiple convolutional layers, and compress multiple values from a single region into a single value to achieve dimension reduction, enhance computational efficiency and prevent overfitting. Common pooling functions include max and average pooling, and its computational processes illustrated in Fig. 30.

3.1.3. Fully connected layer

The fully connected layer connects each neuron in the lower layer to all neurons in the upper layer. It multiplies the weights corresponding to all neurons in the upper layer by the cor-

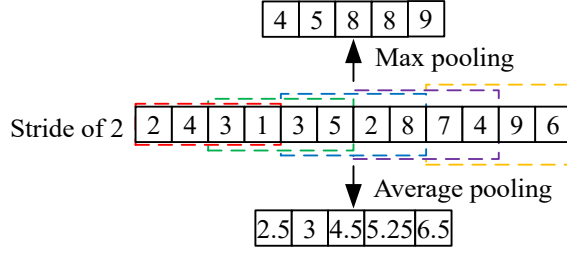


Fig. 30. Pooling operation

responding weights of lower layer neurons, adds the bias value, and integrates the extracted local features, as shown in Eq. (22).

$$y_i = f \left(\sum_{j=1}^{m_x} w_{i,j} \cdot x_j + b_i \right) \quad i = 1, 2, \dots, m_x \quad (22)$$

Where y_i is the output of the i -th neuron in the next layer, m_x is the number of neurons in the next layer, m_s is the number of neurons in the previous layer, $w_{i,j}$ is the weight from the i -th neuron in the next layer to the j -th neuron in the previous layer, x_j is the j -th neuron value in the previous layer, and b_i is the bias value for the i -th neuron in the next layer.

For classification tasks, the computed output y_i is fed into the SoftMax function, which maps it to the probability of belonging to each category, thereby achieving category classification, as shown in Eq. (23).

$$p_c(y_k) = \frac{e^{y_k}}{\sum_{i=1}^{m_x} e^{y_i}} \quad (23)$$

Where $p_c(y_k)$ is the probability of belonging to class k , and y_k is the output of the unit corresponding to class k .

3.1.4. Cross-entropy loss function

The cross-entropy loss function measures the error between predicted and actual values. Through gradient descent and backpropagation of errors, it iteratively updates model parameters to minimize error. Typically, true labels are represented in one-hot encoding format, and the cross-entropy loss function is shown in Eq. (24). Since the cross-entropy function updates weights and biases through backpropagation, it is differentiable with respect to the neuron input y_j , and the partial derivative is expressed as in Eq. (25).

$$L_c = - \sum_{k=1}^{m_x} t_k \log(p_c(y_k)) \quad (24)$$

Where t_k is the sample true label.

$$\begin{aligned}
\frac{\partial L_c}{\partial y_j} &= \sum_{k=1}^{m_x} \frac{\partial L_c}{\partial p_c(y_k)} \frac{\partial p_c(y_k)}{y_j} = \frac{\partial L_c}{\partial p_c(y_j)} \frac{\partial p_c(y_j)}{\partial y_j} + \sum_{k \neq j}^{m_x} \frac{\partial L_c}{\partial p_c(y_k)} \frac{\partial p_c(y_k)}{\partial y_j} = \\
&= -\frac{t_j}{p_c(y_j)} p_c(y_j) (1 - p_c(y_j)) + \sum_{k \neq j}^{m_x} \left(-\frac{t_k}{p_c(y_k)} \right) (-p_c(y_j) p_c(y_k)) = \\
&= -t_j (1 - p_c(y_j)) + \sum_{k \neq j}^{m_x} t_k p_c(y_j) = \frac{e^{y_j}}{\sum_{i=1}^{m_x} e^{y_i}} - t_j
\end{aligned} \tag{25}$$

3.1.5. Batch standardization

In each iteration, the deep network randomly selects a certain number of training samples as inputs and performs forward and backward propagation calculations. However, the distribution characteristics of the selected training samples continuously change during the iteration process, leading to the issue of covariance drift within the network. To address this issue, batch normalization is embedded between layers within the deep network, thereby enhancing convergence speed and generalization, and its specific computational process is detailed in Eq. (26) to (29).

$$\mu_c = \frac{1}{N_b} \sum_{j=1}^{N_b} x_j \tag{26}$$

$$\sigma_c^2 = \frac{1}{N_b} \sum_{j=1}^{N_b} (x_j - \mu_c)^2 \tag{27}$$

$$z_j = \frac{x_j - \mu_c}{\sqrt{\sigma_c^2 + \varepsilon_c}} \tag{28}$$

$$py_j = \gamma_c \cdot z_j + \beta_c \tag{29}$$

Where x_j is a feature dimension of the j -th sample, N_b is the number of batch processing units, py_j is corresponded to the batch processing output for a specific feature dimension of the j -th sample, γ_c is the scaling factor, β_c is the offset coefficient.

3.1.6. Residual module

The residual module is illustrated in Fig. 31. Residual module A is comprised two convolutional layers, two ReLU, two batch standardizations, and one identity mapping. The sum of the input and output serves as the input for subsequent network layer. This amplifies the residual between input and output, thereby reducing the network training difficulty and enhancing the model expressive capability. Residual module B differs from A by incorporating a convolutional layer within the identity mapping. When the convolutional layer within residual module B employs a convolutional kernel with a specific stride to reduce the input data dimension, the identity mapping is correspondingly configured with a convolutional layer for data dimension reduction, which ensures the main path and identity mapping maintain identical dimensions [31].

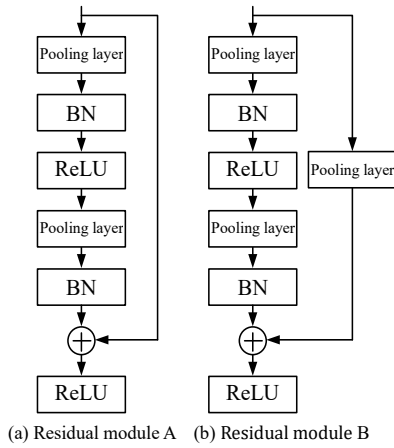


Fig. 31. Residual module

3.2. Modelling

Rich SD features are included within the displacement, acceleration, angular displacement of HC, and buffer relative displacement [27]. To enhance the SDI accuracy, the signal undergoes feature-level fusion [30], and the fusion model is depicted in Fig. 32. AITQWPT is employed for

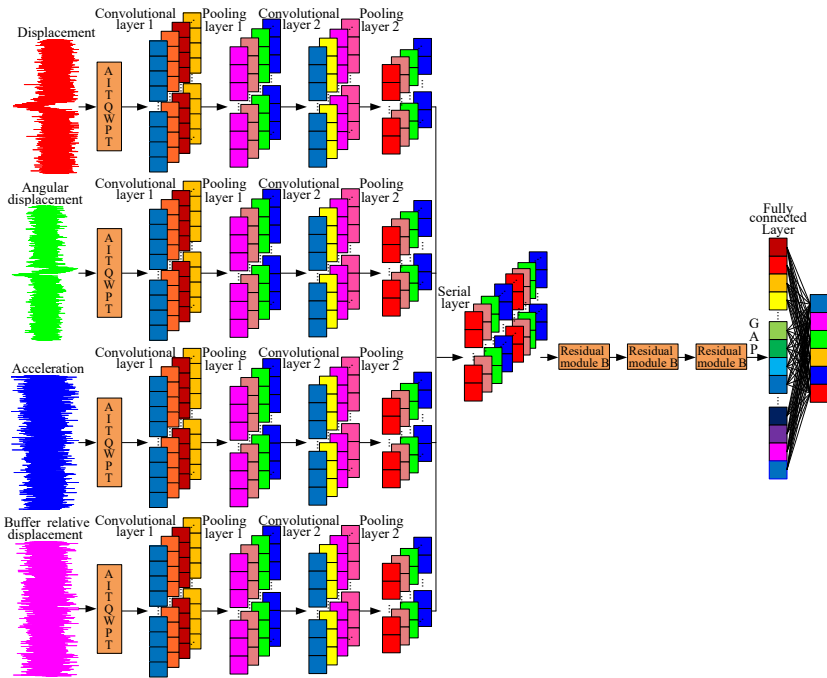


Fig. 32. Shaft deformation identification model of multi-sensor data fusion

noise reduction, and the normalized data is used to minimize deviations among diverse SD. The denoised data is then fed into a residual convolutional neural network to achieve SDI. The model is comprised two convolutional layers, two pooling layers, one serial layer, three residual modules, one global average pooling layer, and one fully connected layer. The first two convolutional layers extract shallow features from the signal, and its dimension is then reduced by pooling layer. The shallow features undergo feature-level fusion through a serial layer, and the fused features subsequently pass through three residual modules for deep feature extraction, which serves as input to a fully connected layer and then performs SDI through SoftMax function. The data length is 5650, and the output category has 6 types, corresponding to the aforementioned 5 types and undeformed state. The network model parameters are shown in TABLE 3.

TABLE 3

Identification model parameters for multi-sensor data fusion

Type	Kernal size/stride/number	Input size	Output size
Convolutional layer 1	7×1/1/16	5650×1@1	5650×1@16
Pooling layer 1	2×1/2/16	5650×1@16	2825×1@16
Convolutional layer 2	5×1/1/32	2825×1@16	2825×1@32
Pooling layer 2	2×1/2/32	2825×1@32	1413×1@32
Serial layer	—	1413×1@32	1413×1@128
Residual module B	$\begin{pmatrix} 3 \times 1/2/32 \\ 3 \times 1/1/32 \end{pmatrix}$	1413×1@160	707×1@32
Residual module B	$\begin{pmatrix} 3 \times 1/2/64 \\ 3 \times 1/1/64 \end{pmatrix}$	707×1@32	354×1@64
Residual module B	$\begin{pmatrix} 3 \times 1/2/128 \\ 3 \times 1/1/128 \end{pmatrix}$	354×1@64	177×1@128
Global average pooling layer	177×1	177×1@128	128×1@1
Fully connected layer	—	128×1@1	6×1@1

3.3. Model validation

HC Displacement, angular displacement, acceleration, and buffer relative displacement are collected via the mine winding hoisting system dynamic simulation model in Fig. 6 and the experimental platform in Fig. 27. The SD characteristics are obscured by manually adding noise, and the signal-to-noise ratios range from −15 to 0 dB. Six SD labels are assigned, and these labels are encoded using one-hot vectors. The sample number is 1000, and 800 samples are randomly selected as the training set and the remaining 200 samples as the test set. The training set is used to train the model, while the test set is used to evaluate its performance. The model training batch size is 96, the training epoch is 50, model parameters are updated using the Adam algorithm, the initial learning rate is 0.001, the learning rate decay factor is 0.1, and the decay period is 10. The training process is repeated 10 times, and the model performance is evaluated by the average accuracy and loss across all 10 training iterations. The classification accuracy and loss curves for the multi-sensor data fusion model is showed in Fig. 33.

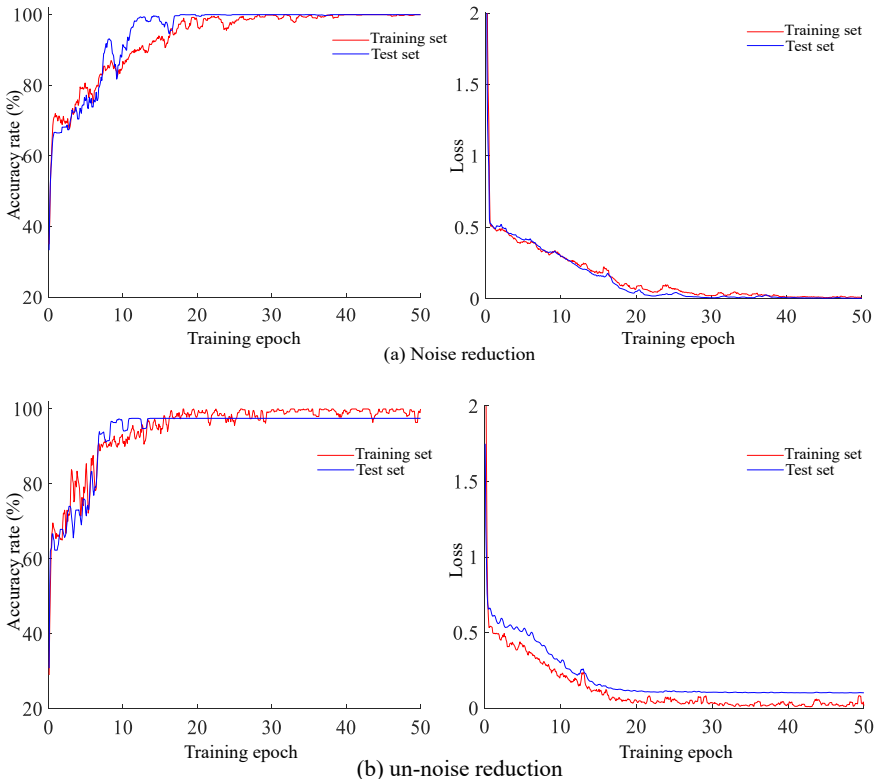


Fig. 33. Accuracy and loss values for shaft deformation identification model of multi-sensor data fusion

From Fig. 33, it can be observed that as the training epoch increases, the classification accuracy of the training set is 100%, the denoising test set reaches 100%, and the un-denoising test set also reaches 97.5%. After a certain number of training epoch, it all reach a stable state. Furthermore, the classification confusion matrix of test set in Fig. 34 reveals that misclassifications primarily occur in SBD, SDD, and SHSD, which is mainly due to the relatively weak deformation features and is easily obscured by noise. The training set accuracy stabilizes at the 39th epoch, and the loss function decreased to 0.012. In contrast, the accuracy of the un-denoised training set is fluctuated, and the fluctuation degree is diminished as training epoch augmentation. It remained unstable even by the 50th epoch, its loss function still at 0.028, and its test set classification accuracy is lower than that of the denoised test set. The above analysis demonstrates the feasibility and effectiveness of the multi-sensor data fusion model for SDI, while also highlighting the superior denoising performance of AITQWPT. To further validate the model effectiveness of SDI, its classification results is compared with those from single-input convolutional neural network, residual network, a multi-sensor data fusion convolutional neural network as shown in TABLE 4. The classification accuracy of the multi-sensor data fusion model significantly outperforms single-input models. Moreover, the classification accuracy is heightened compared to the un-denoised data, which demonstrates the outstanding classification performance and validity of the proposed model.

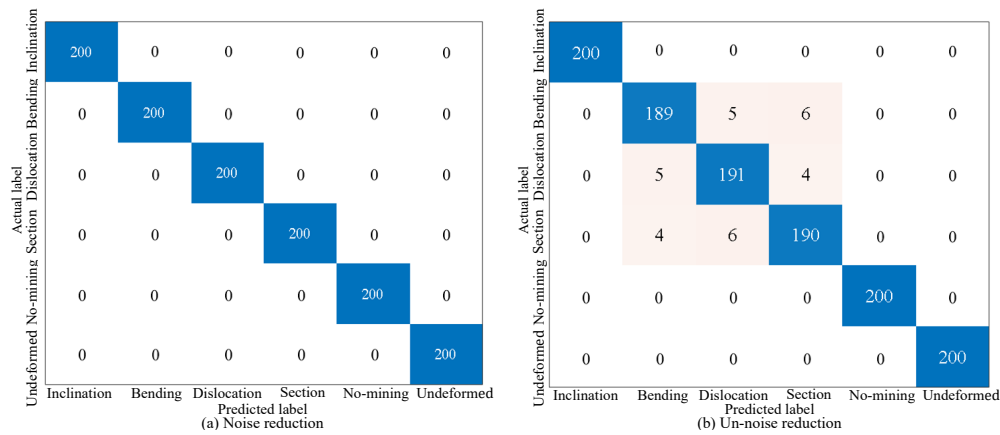


Fig. 34. Classification confusion matrix of test set

TABLE 4

Accuracy of diverse classification model

Type	Classification accuracy without noise reduction (%)	Classification accuracy under noise reduction (%)
Single-input convolutional neural network	83.75	87
Single-input residual network	84	86
A multi-sensor data fusion convolutional neural network	90.5	93
Proposed method	97.5	100

4. Conclusion

To validate the SDI feasibility using HCOC and heighten identification accuracy, a noise reduction algorithm based on AITQWPT is proposed, and a multi-sensor data fusion model of SDI is established on the above basis. Its effectiveness is verified through simulation and experimental data, and the following conclusions are obtained:

- (1) The noise reduction algorithm effectively suppresses interference components of HCOC, highlights SD features, and significantly improves SNR and RMSE. Its denoising performance is outstanding and stable, and it is significantly superior to other noise reduction methods.
- (2) Multi-sensor data fusion model integrates SD features from HC displacement, angular displacement, acceleration, and buffer relative displacement, which accomplishes complementary feature information, and reduces the number of layers and complexity of the residual convolutional neural network, and enhances the SDI accuracy.
- (3) The SDI model demonstrates the deformation recognition feasibility through HCOC, which enables real-time dynamic monitoring of the entire shaft structure without requiring structural modifications or interrupting normal production, and lays the theoretical foundation for accelerating its industrial application.

- (4) The paper completes offline validation of the algorithm and recognition model only under static, single-deformation conditions; it did not consider coupled deformation conditions where bending, torsion, and tension coexist in the shaft, and thus remains some distance from medium- to long-term online engineering applications underground. In the future, the coupled multi-deformation conditions will further investigate, optimize the model for lightweight implementation and enable embedded deployment, develop a medium- to long-term online monitoring system for coal mine shafts, and simultaneously advance underground field trials to continuously refine the on-site deployment plan and enhance the engineering practical value of these findings.

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