Research Article

Digital Twin Inspired Intelligent Bearing Fault Diagnosis Method Based on Adaptive Correlation Filtering and Improved SAE Classification Model

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1. Introduction

Rolling bearing is a common device that is widely used in rotating machineries, such as motors, pumps, and gears. Rolling bearing faults may bring serious accidents that can result in property damage and personal injury [1, 2]. Thus, an accurate diagnosis of the rolling bearing fault has important significance for the safety of industrial production equipment.

At present, many studies have focused on bearing fault diagnosis [3–5], and the use of vibration signal as a diagnostic signal is one of the main methods. The key steps of the diagnosis method based on vibration signal include the extraction of the signal characteristics in the time and frequency domains or time–frequency domain. Recently, studies have indicated two kinds of bearing diagnosis methods: one is data-driven pattern recognition-based method, and the other one is bearing fault mechanism-based method [6]. The process of bearing fault mechanism-based method is detailed as follows: the vibration signal in bearing is acquired, and the fault characteristic frequency is extracted by signal processing. According to the fault characteristic frequency in the diagnosis signal, the dominant characteristic frequency in the signal is compared, and then the bearing is judged whether it has faults [7]. The signal processing methods include signal denoising and signal fault enhancement. Signal denoising includes high-pass, low-pass, or band-pass filtering [8], Kalman filtering, morphological filtering [9], wavelet denoising [10], and particle filtering, etc. Signal fault enhancement uses signal decomposition or stochastic resonance methods to extract or enhance fault signals. The signal decomposition methods include empirical mode decomposition [11, 12], variational modal decomposition [13], and intrinsic time scale...
decomposition [14]. These methods can effectively extract the signal fault feature components. However, the methods heavily rely on the understanding of the mechanism. Moreover, different working and load conditions will affect the applications of the bearing and the method.

Another data-driven pattern recognition-based method extracts the characteristic parameters, such as variance, skewness, kurtosis, spectral kurtosis, and other characteristic parameters, from different signal domains (e.g., time, frequency, time–frequency) [13, 15], and then uses various modeling methods to establish an effective discrimination model based on the characteristic parameters for diagnosis. Such approaches often combine the commonly used methods, such as principal component analysis, independent component analysis, artificial neural network, K-nearest neighbor algorithm, and other intelligent methods, in machine learning [16]. With the development of deep learning, many methods, such as convolutional neural networks and deep belief networks, have been used to establish bearing fault discrimination models [17]. However, in engineering application, the pattern recognition method-based approach shows its limitations. The bearing fault can be diagnosed correctly depending on the accuracy of the diagnosis model, and the key to the accuracy of the diagnosis model is the effective extraction of fault signal features, which largely depend on the signal filtering method. In the whole operation, if the effect of any processes is not ideal, then it will not extract effective fault features, which will result in low diagnosis accuracy.

Based on previous research, the rotating machinery rolling bearing fault signal extraction technology still needs further improvement. Recently, digital twin is emerging as a key technology for rotating machinery intelligent operation and maintenance and provides a new method for bearing fault diagnosis. Literature [18] proposed a bearing lifecycle digital twin model driven by the data-model combination, and it was used for bearing degradation performance analysis and health management. In [19], the B-spline fitting displacement excitation method was presented to replace the traditional displacement excitation function to represent the fault excitation in high-speed angular contact ball bearing fault dynamic model. Digital twins have been well applied in expanding training data for machine learning, [20] developed a numerical model of a rotor-ball bearing system, and [21] used it for bearing anomaly detection and crack size identification. Literature [22] uses digital twin technology to simulate a large number of balanced datasets to train the model, and the trained model can be migrated to a physical production line for fault diagnosis through transfer learning. This method was verified on the basis of an automotive rear axle assembly line, and the algorithm achieved an accuracy rate of 97.8%. In [23], the application of intelligent digital twin combined with the machine learning for bearing anomaly detection and crack size identification was proposed. The intelligent digital twin was designed on the basis of Kalman filter, high-order variable structure technique, and adaptive neurofuzzy technique for generating residual signals. The results of the validation experiments on the bearing data from Case Western Reserve University (CWRU) show that the average accuracy of bearing fault recognition and crack size recognition are 99.5% and 99.6%, respectively.

Therefore, this study presents a digital twin inspired intelligent bearing fault diagnosis method based on adaptive correlation filtering and improved stack autoencoder (SAE) classification model. First, the raw engineering signal is filtered by adaptive correlation filtering, in which the cut-off frequency is preferred on the basis of the maximum similarity between the simulated spectrum and the engineering spectrum. Before that, the simulation model in the virtual space is adjusted using parameters, such as the speed, sampling frequency, and theoretical fault characteristic frequency of the acquired physical entity engineering signal. Subsequently, the filtered signal is inputted into the improved SAE (ISAE) [24] model for the diagnosis of rotating machinery rolling bearing faults. Finally, the engineering and comparison experiments are proposed to prove the effectiveness and accuracy of the proposed diagnosis method.

The main contributions of this study are as follows:

1. A novel intelligent bearing fault diagnosis inspired by the interactive cointegration of physical entities and virtual space is presented in digital twins

2. Adaptive correlation filtering is designed to use virtual space spectrum as the best target for engineering signal filtering.

3. A new activation function is proposed for improving the SAE model to avoid slow convergence of the network

The rest of the paper is organized as follows. Section 2 introduces digital twin inspired intelligent bearing fault diagnosis model. Section 3 defines the adaptive correlation filtering. Section 4 describes the improved SAE classification model. Section 5 gives the virtual space bearing fault simulation model. Section 6 presents the rotating machinery rolling bearing faults intelligent diagnosis method. Section 7 shows the experimental results. Section 8 summarizes the conclusion.

2. Digital Twin Inspired Intelligent Bearing Fault Diagnosis Model

Bearing is the most common and important mechanical parts of rotating machinery; once it faults, the machinery may cause serious accidents that will result in property damage [25, 26]. Inspired by digital twin, the information sharing of ideal bearing fault signals in virtual space and engineering signals in physical space is realized so that an intelligent bearing fault diagnosis model can be designed. As shown in Figure 1, the first step is to adjust the simulation model (in virtual space) through physical entity parameters, such as RPM, theoretical fault characteristic frequency, and sampling frequency of the acquired signal; and then the ideal simulated no-noise spectrum is fed back to the adaptive correlation filtering for the preferred cut-off frequency; finally, the best filtered signal is obtained for the intelligent diagnosis of bearing fault.
3. Adaptive Correlation Filtering

High-pass filtering has the advantages of small calculation, clear structure and physical meaning, and short running time. It has attenuation effect on the components below the cut-off frequency and is more commonly used in bearing vibration signal processing. However, the selection of cut-off frequency, which directly determines the effect of filtering, is particularly important. The traditional cut-off frequency setting relies on manual experience, and it often leads to unstable filtering results. Therefore, this study designs an adaptive correlation filtering that can prefer the cut-off frequency adaptively.

For one-dimensional vibration signal acquired by an accelerometer, the signal can be expressed as

\[ X = [x_1, x_2, \ldots, x_i, x_{i+1}, \ldots, x_N]. \]  

(1)

The upper limit \( y_1 \) and lower limit \( y_2 \) of the cut-off frequency are set, and high-pass filtering is performed on \( X \) with a step size \( \tau \) within this range:

\[ F(X) = HPF(X), y = y_1 + nr, \]  

(2)

where \( HPF \) represents high-pass filtering, and \( n = (y_2 - y_1)/\tau \).

In the above step, the similarity value between each filtered spectrum \( S_e \) and the simulated spectrum \( S_v \) is calculated, and the maximum value is used as the preferred condition for screening the best cut-off frequency.

\[ Corr = \frac{E[(S_e - \bar{S}_e)(S_v - \bar{S}_v)]}{\sqrt{E[(S_e - \bar{S}_e)^2]E[(S_v - \bar{S}_v)^2]}}. \]  

(3)

4. Improved SAE Classification Model

Autoencoder (AE) refers to an unsupervised learning algorithm. It attempts to learn a function so that the output value is approximately equal to the input value. It is composed of an input layer, a hidden layer, and an output layer. Its network structure is shown in Figure 2.

The input and hidden layers form a coding network. The encoding process aims to convert \( n \)-dimensional input data into \( m \)-dimensional hidden layer expression with advanced features. The hidden and output layers form an encoding network, and the decoding process reconstructs the output data \( y = (y_1, y_2, y_3, \ldots, y_m) \) for the hidden layer vector.

The encoding and decoding processes can be expressed by the following:

\[ h = f(W_x x + b_1), \]

\[ y = g(W_h h + b_2). \]  

(4)

where \( f \) is the encoding activation function, \( g \) is the decoding activation function, \( b_1, b_2 \) is the bias, and \( W_x, W_h \) is the weight matrix \( W_h = W_x^T \).

AE iteratively optimizes the parameter set through backpropagation and gradient descent algorithm until the reconstruction error is minimized, and the reconstruction error function is expressed as follows:

\[ J_{MSE}(\theta) = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{1}{2} || y_i - x_i ||^2 \right). \]  

(5)

For SAE classification models, activation functions are important factors in determining whether the model is good or not. However, the commonly used sigmoid function
causes gradient disappearance easily. To improve the activation function, ReLTanh [27] and Isigmoid [28, 29] methods are used. Although these methods can improve the performance of the activation function, the complexity of the algorithm and the speed of convergence increased. To solve this problem, this study proposes a new activation function: the Tan function. The mathematical form of the Tan function and its derivative function is expressed as follows:

\[ f_2(x) = \tan(x)/\tan(1), \]
\[ g_2(x) = \sec^2(x)/\tan(1). \]  

Figure 3 shows the curves of the sigmoid and Tan functions. When the input of the neurons is far from zero, the sigmoid derivative value will become very small, approximatetozero, therebyresultinginthelowspeedofconvergenceofthenetworkmodel; that is, the gradient disappears; and in the Tan function, the minimum value of the derivative is approximately 0.64, which will not appear as 0, thereby resulting in the disappearance of the gradient and faster convergence of the model.

Iterate the function and update the \( e(x, y) \) until the \( e(x, y) \) converges.

SAE is stacked by multiple AEs in series, and the improved SAE classification model is shown in Figure 4.

5. Bearing Fault Model in Virtual Space

Bearing fault simulation model is established on the basis of MATLAB software. This model can simulate outer race fault, inner race fault, and roller fault. The bearing fault simulated spectrum generated in the virtual space is used as the optimal target in the adaptive correlation filtering.

5.1. Outer Race Fault. The bearing outer race fault simulate equation is shown in equation (7), where \( f_0 \) represents the characteristic frequency, \( N_0 \) is the RPM, \( \xi_0 \) is the damping ratio, and \( f_{01} \) and \( f_{02} \) are the different carrier center frequencies.

\[
f(t) = \sum_{i=1}^{N_0} \left[ \sin 2\pi (t - \xi_0 f_{0n}) \left(1 - \xi_0^2 f_{0n}^2 (t - \xi_0 f_{0n}) \right) + f_{02}^e \right] \cos 2\pi f_{0n} (t - \xi_0 f_{0n}) \right].
\](7)

5.2. Inner Race Fault. Equations (8) and (9) show the bearing inner race fault simulation model, where \( f_{s}\) is the rotational frequency, \( T \) is the fault characteristic period, \( \tau_k \) is the \( k \)th shock fluctuation, \( c \) is the signal damping index, and \( f_n \) is the resonance frequency.

\[
f(t) = A(1 - B \cos(2\pi f_{s} t)) \cos(2\pi f_n (t - \xi_0 f_{0n})).
\]  

5.3. Roller Fault. Equation (10) shows the bearing roller fault simulation model, where \( d_0 \) is the amplitude, \( T_f \) is the repetition period, \( A_{k}^f \) is the amplitude of the \( k \)th harmonic;
6. Proposed Intelligent Diagnosis Method

This study presented a digital twin inspired intelligent bearing fault diagnosis method based on adaptive correlation filtering and improved SAE classification model. The detailed process is shown in Figure 6, and the specific steps are given as follows:

Step 1: the vibration signal is acquired by using the accelerometer under the real bearing, and the kurtosis is calculated for the simple diagnosis of bearing fault.

Step 2: the sampling frequency, data length, theoretical fault characteristic frequency, RPM, and other parameters of the vibration signal are inputted to the simulation model.

Step 3: the simulation model outputs three corresponding noise-free simulation signals types for outer race fault, inner race fault, and roller fault.

Step 4: adaptive correlation filtering is performed on the vibration signal in physical space, where the maximum similarity between the simulated and acquired spectra is the preferred condition for the optimal cut-off frequency.

Step 5: an improved SAE classification model is built, and the spectra of normal and three fault states are fed into the ISAE model for training.

Step 6: the test samples are inputted to diagnose the rotating machinery rolling bearing fault types.

7. Experimental Verification

7.1. Experiment Platform. The experimental platform shown in Figure 7 is used for acquiring bearing vibration signals to verify the effectiveness of the proposed bearing fault intelligent diagnosis method. This platform includes motor, coupling, bearing, bearing base, and rotating shaft. It can realize the speed adjustment in the range of 300 RPM–3000 RPM and can carry out the experiments of bearing outer race fault, inner race fault, and roller fault. During the experiment, the acceleration sensor is placed directly above the bearing to acquire the vibration signal.

The vibration signal and its spectrum in the normal state of the bearing are shown in Figure 8, where the speed is 1000 RPM, and the sampling frequency is 100 kHz. Affected by the working environment, the vibration signal contains background noise, which can be seen from the spectrum in Figure 8(b), and the background noise is concentrated in the low-frequency region. Therefore, selecting the high-pass filtering in this study is reasonable.

7.2. Outer Race Fault Experiment. In the outer race fault experiment, the size of the fault is 0.25 mm × 0.7 mm (depth × width), the speed is 1000 RPM, and the sampling frequency is 100 kHz, and the theoretical fault characteristic frequency is 66.5 Hz. The original vibration signal and its spectrum are shown in Figure 9. The regular impacts generated by the bearing fault are drowned by the background noise, and the dominant frequency in the spectrum drowns out the fault characteristic frequency, thereby making it impossible to realize fault diagnosis.

The simulated spectrum of the bearing outer race fault in the virtual space is used as the comparison reference, and the vibration signal in the physical space is filtered by adaptive correlation filtering, where the best high-pass filtering cut-off frequency with the maximum similarity between the simulated spectrum and the filtered spectrum is preferred. In this experiment, the cut-off frequency search range is set to 500–5000 Hz, and the step size is set to 100 Hz. Figure 10(a)
shows the curve of the similarity with the change in the cut-off frequency in the adaptive correlation filtering. The similarity is maximum when the cut-off frequency of the high-pass filtering is set to 4200 Hz, and the filtering effect is best at this time, as shown in Figure 10(b). The actual fault characteristic frequency is basically the same as the theoretical fault characteristic frequency, and the amplitude of the dominant frequency and its harmonics are much higher than the other frequency components. Compared with Figure 9(b), the background noise in the vibration signal has been suppressed significantly, and the accurate extraction of the fault characteristic frequency of the outer race fault can be achieved.

The similarity between the filtered spectrum and the simulated spectrum for different cut-off frequencies is shown in Table 2. Combined with the similarity curve in Figure 10(a), the similarity gradually increases between 0 and 4200 Hz (at 4200 Hz, the similarity is 0.4918) and then gradually decreases.

Figure 11 shows the spectrum of the high-pass filtered signal at different cut-off frequencies. The noise in the spectrum gradually decreases with the increase in the cut-off frequency, and the amplitude of the actual fault characteristic frequency and its harmonic gradually increases, indicating that the adaptive correlation filtering proposed in this study is effective.
7.3. Inner Race Fault and Roller Fault Experiment. In the bearing inner race fault and roller fault experiments, the experimental conditions, such as the size of the fault, RPM, and sampling frequency, are the same as those in the outer race fault experiments. In this experiment, the cut-off frequency search range is set to 500–5000 Hz, and the step size is set to 100 Hz. Among them, the theoretical fault characteristic frequency of the inner race fault is 110.1 Hz, and the original vibration signal and its spectrum are shown in Figure 12. Similar to the outer race fault, the vibration signal of the inner race fault also contains a large amount of background noise, and the fault characteristics are drowned, so that fault diagnosis cannot be realized.

Figure 13(a) shows the similarity curve between the virtual space spectrum and the physical space spectrum in the adaptive correlation filtering. Figure 13(a) shows that the similarity is the largest at 0.5693 when the cut-off frequency is 3200 Hz. Figure 13(b) shows the best filtered spectrum, and compared with Figure 12(b), the amplitude of fault characteristic frequency and its harmonic are significantly increased.
higher than the side frequency, and the background noise is suppressed effectively. It indicates that the adaptive correlation filtering proposed in this study is equally effective in the bearing inner race fault experiments.

In the bearing roller fault experiment, the theoretical fault characteristic frequency is 79.3 Hz. The original vibration signal and its spectrum are shown in Figure 14. As in the case of the outer race fault and inner race fault, the fault characteristic frequency in Figure 14(b) was drowned by noise, and the fault could not be identified effectively.

| Cut-off frequency (Hz) | Corr  |
|-----------------------|-------|
| 0                     | 0.3451|
| 500                   | 0.3578|
| 1000                  | 0.4046|
| 2000                  | 0.3829|
| 3000                  | 0.4718|
| 4000                  | 0.4881|
| 4500                  | 0.4884|
| 5000                  | 0.4880|
Figure 15(a) shows the similarity curve in the roller fault experiment, and Figure 15(b) shows the best filtered spectrum. The cut-off frequency is 5000 Hz when the filtering effect is the best. The fault characteristic frequency and its harmonics in Figure 15(b) can be extracted accurately, showing that the adaptive correlation filtering proposed in this study is also effective in the bearing roller fault experiment.

To realize the intelligent diagnosis of bearing faults, this study uses the improved SAE algorithm to establish the classification model. In the experiment, the signals in four states of bearing normal, outer race fault, inner race fault, and roller fault are extracted. A total of 40 sets of signals are extracted for each type, and the spectrum is extracted after adaptive correlation filtering of the signals and then inputted to the ISAE model for training. In addition, 10 sets of signals
Figure 13: The curve of the similarity in adaptive correlation filtering and its optimal spectrum: (a) curve of the similarity; (b) spectrum.

Figure 14: Vibration signal and its spectrum of roller fault: (a) vibration signal; (b) spectrum.

Figure 15: The curve of the similarity in adaptive correlation filtering and its optimal spectrum: (a) curve of the similarity; (b) spectrum.
are extracted for each type for validation, and the results are shown in Figure 16. The recognition rate of the ISAE classification model is 100%. All four fault types are correctly classified, indicating that the intelligent bearing fault diagnosis method based on the adaptive correlation filtering and ISAE proposed in this study is effective.

To verify the necessity of adaptive correlation filtering in the intelligent bearing fault diagnosis method, the original signal and the filtered signal (with a cut-off frequency of 1500 Hz) were used for comparison, and the results are shown in Figure 17. In Figure 17(a), the spectrum of the original signal is inputted into the ISAE model, and the correct diagnosis rate is only 72.5%. In Figure 17(b), the cut-off frequency of 1500 Hz is set to filter the original signal, and the ISAE recognition result is improved relative to the original signal, but the correct rate is still only 95%, which is lower than that of the adaptive correlation filtering. It indicates that the adaptive correlation filtering can remove the background noise effectively and improve the correct rate of intelligent diagnosis of bearing faults.

Table 3 shows the effects of different numbers of hidden layers on the recognition results in the ISAE classification model. With the change in the number of hidden layers, the recognition rate of ISAE changes, but on the basis of ensuring the recognition rate, the computation time of the algorithm is reduced as much as possible to ensure the recognition stability of the algorithm. Therefore, the first hidden layer of ISAE is set to 100, the second is set to 20, and the third is set to 10 in this study.

Figure 18 shows the comparison of recognition results of different classification models. To avoid the chance of the algorithm recognition results and thus affect the evaluation of the algorithm effectiveness, 10 times of diagnosis results are counted in this study. Figure 18 shows that the ISAE model has the highest recognition rate, the smallest variance of the 10 results, and the most stable performance.

Table 4 shows the minimum time, maximum time, and average time of the different classification models in 10 runs. The running time of the ISAE model is relatively stable and within the acceptable range.
7.4. CWRU Bearing Data Experiment. In this study, the bearing fault experimental data of CWRU are employed to verify the effectiveness of the proposed method. The experimental platform device (in Figure 19) is depicted as follows.

Table 5: Basic experimental conditions and theoretical fault characteristic frequencies.

| Type                      | Parameter          | Value   |
|---------------------------|--------------------|---------|
| Experimental conditions   | RPM                | 1797    |
|                           | Sampling frequency | 12000   |
|                           | Length of signal   | 16384   |
| Theoretical fault         | Outer race fault   | 91.4 Hz |
|                           | Inner race fault   | 147.9 Hz|
|                           | Roller fault       | 119.2 Hz|

Table 5 shows the basic experimental conditions and theoretical fault characteristic frequencies that correspond to the signal used in this experiment. In the experiment, the faulty bearing is located at the fan end of the motor, and the sensor position is directly above the bearing in the case of inner race fault and roller fault, and in the case of outer race
Figure 20: Vibration signal and its spectrum under the four states: (a) normal bearing; (b) outer race fault; (c) inner race fault; (d) roller fault.
The sensor position is at the 3-o’clock direction of the bearing.

Figure 20 shows the vibration signal and its spectrum under normal bearing, outer race fault, inner race fault, and roller fault. The figure shows that the background noise drowns out the regular impact caused by the bearing fault, and the fault characteristic frequency cannot be extracted from the spectrum accurately.

Adaptive correlation filtering is performed on the original signal, and Table 6 shows the optimal cut-off frequencies and similarity that corresponds to the outer race fault, inner race fault, and roller fault. The spectrum of the best filtered signal is shown in Figure 21. Referring to Table 5, the dominant frequencies in each spectrum are basically the same as the theoretical fault characteristic frequencies, and the amplitudes of fault characteristic frequencies and their harmonics are much higher than the other frequency components. It indicates that the adaptive correlation filtering is also effective for CWRU signals.

Figure 22 shows the recognition results of the improved SAE classification model, from which the normal and three faults of the bearings are correctly classified with a recognition rate of 100%. This finding proves that the intelligent bearing fault diagnosis method based on adaptive correlation filtering and improved SAE classification model
proposed in this study are equally effective for CWRU experimental signal.

7.5. Comparison Experiment. To verify the advantages of the adaptive correlation filtering and the improved SAE method presented in this study, three comparative experiments were carried out on the basis of the experimental platform shown in Figure 7.

7.5.1. Comparison with Kurtosis-Based Filtering. The spectral kurtosis of the vibration signal (under bearing inner race fault) is shown in Figure 23(a), the kurtosis maximum (115.479) occurs at level 5 and at an optimal window length equal to 64, where the center frequency is 28.9063 kHz, and the bandwidth is 1.5625 kHz. The band-pass filter is set according to the spectral kurtosis result, and the spectrum of the kurtosis-based filtered signal is shown in Figure 23(b). Compared with the spectrum of the adaptive correlation filtered signal, the noise is larger in the kurtosis-based filtering method, although it can extract fault characteristic frequencies.

7.5.2. Comparison with Different Activation Functions. Four different activation functions, namely, sigmoid, Tan, Rel.Tanh, and Isigmoid, are used for comparison, and three indicators, such as accuracy, running time, and convergence speed, are compared. The results are shown in Table 7. Table 7 shows that, under the same operating conditions, the convergence speed of sigmoid is slower, and the accuracy is lower. Although Rel.Tanh and Isigmoid can achieve the same accuracy, the running time is longer than Tan.

Table 7: Result of using different activation function.

| Activation function | Accuracy (%) | Run time (s) | Convergent iteration |
|---------------------|--------------|--------------|----------------------|
| Sigmoid             | 97.5 ± 2.237 | 10.91        | 900 ± 59             |
| Tan                 | 99.5 ± 1     | 10.85        | 412 ± 25             |
| Rel.Tanh            | 99 ± 1.658   | 21.62        | 453 ± 39             |
| Isigmoid            | 99.5 ± 1     | 19.33        | 389 ± 36             |

![Figure 23: Spectral kurtosis and spectrum: (a) spectral kurtosis; (b) spectrum under different filtering.](image)

![Figure 24: Identification results under different filtering methods.](image)
Therefore, it proved that the Tan activation function has advantages using in bearing fault diagnosis.

7.5.3. Compared with Decomposition-Based Filtering Method. Three methods of empirical mode decomposition (EMD), local mean decomposition (LMD), and variational mode decomposition (VMD) are used to decompose the vibration signal, and the IMF 1 is extracted as the filtered signal, which is input into the improved SAE classification model for training and testing. For a more accurate comparison, 10 SAE recognition results were counted, as shown in Figure 24. It can be seen from the results that the method proposed in this paper has the highest diagnostic accuracy and the best stability.

8. Conclusion

This study presented a digital twin inspired intelligent diagnosis of rolling bearing faults based on adaptive correlation filtering and improved SAE classification model. The engineering experiments and comparisons proved the following:

1. Based on the simulation model in the virtual space to achieve the optimal cut-off frequency of adaptive filtering, the best filtering effect can be obtained without excessive a priori knowledge, which is more suitable for engineering applications.

2. Improved SAE has the characteristics of feature extraction and pattern recognition and has strong multiclassification capabilities. Combined with the improved SAE classification model, the intelligent diagnosis method presented in this paper can achieve a 100% accuracy rate.

3. The results of the comparison with CWRU proved the higher effectiveness of this intelligent diagnosis method.

Further research should focus on establishing the bearing fault dynamic mode in virtual space to map the whole lifecycle of physical equipment and expand the training samples for fault diagnosis and realize the engineering value of digital twin better.

Data Availability

The raw/processed data required cannot be shared at this time as the data also form part of an ongoing study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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