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A Novel Roller Bearing Condition Monitoring Method Based on RHLCD and FVPMCD

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ABSTRACT Effective condition monitoring provides some benefits such as improving safety and reliability. Roller bearing is the key component of rotating machinery, and a novel roller bearing condition monitoring method based on rational Hermite interpolation-local characteristic-scale decomposition (RHLCD) and fusion variable predictive model-based class discriminate method (FVPMCD) is proposed in this paper. RHLCD can adaptively decompose any complex signal into a sum of rational intrinsic scale components (RISCs), whose instantaneous frequency has physical meaning. In addition, targeting the limitation of variable predictive model-based class discriminate method (VPMCD), FVPMCD is presented. First, four kinds of common models are used to recognize a sample. Then, the recognition results of each model are satisfied, and the recognition probability of each state is calculated. Finally, the largest recognition probability of the state is chosen to recognize categories. The analytical results of experimental signals indicate that the proposed condition monitoring approach can identify the states of roller bearing effectively.

INDEX TERMS Rational Hermite interpolation-local characteristic-scale decomposition, fusion variable predictive model-based class discriminate method, roller bearing, condition monitoring.

I. INTRODUCTION

Roller bearing is the key component of the rotating machinery, whose fault is the common fault of mechanical system. When the failure of roller bearing occurs, it will directly affect the operation of the entire mechanical system. Effective condition monitoring can provide some benefits such as the improved safety and improved reliability, and prevents catastrophic failures in rotating machinery [1,2]. Therefore, how to effectively demonstrate the highly relationship between roller bearing diagnosis inputs and corresponding system health states has become particularly important [3,4].

Nowadays, vibration signal analysis is the most extended technique for condition monitoring. However, the measured vibration signal of roller bearing is nonlinear and non-stationary signal in general, and vibration measurements are usually used in condition monitoring of roller bearings, which can be realized by acceleration sensors. When the faults of the roller bearing occur, the vibration signal of roller bearing would be different from the signal under normal state. Meanwhile, the noise signal and background signal are mixed in the measured signal, and it is difficult to extract the information related with fault effectively from the vibration signal by traditional time-domain and frequency-domain methods based on Fourier transform. Obviously, some limitations are existing in the analysis of non-stationary vibration signal of roller bearing [5], [6].

Aiming at the shortages of the time-domain and frequency-domain method based on traditional Fourier transform, some time-frequency analysis methods have been proposed to analyze non-stationary signal [7], such as empirical mode decomposition (EMD) [8], local mean decomposition (LMD) [9], intrinsic time-scale decomposition method (ITD) [10] and so on. ITD as a typical adaptive time-frequency analysis method, which can obtain several proper rotation components (PRCs) adaptively, whose instantaneous frequency has physical meaning. Meanwhile, ITD overcomes some shortcomings of EMD and LMD methods in computational efficiency, mode mixing and end effect [11]–[14]. Unfortunately, ITD method does not explain

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the physical meaning of the algorithm itself and PRC. In addition, the instantaneous amplitude and frequency of the baseline signal obtained by linear transformation often is distorted [15].

In view of the shortcomings of ITD, the further application will be restricted and some scholars have proposed some improved ITD methods. Cheng et al. used a cubic spline to envelop signals, and then proposed the local characteristic-scale decomposition (LCD) [11]. Bouchikhi et al. used the cubic B-spline interpolation to get a smoother component signal, and removed the burr phenomenon [16]. The cubic spline interpolation method shows superiority in convergence and smoothness, but it is easy to produce the problems of under-envelope and super-envelope, especially strong impact non-stationary signals. To solve the problem of cubic spline interpolation, Li et al. applied the Hermite interpolation to ITD method [17], which has a characteristic of shape preservation, and this method is superior to the analysis of strong impact non-stationary signals. However, the cubic Hermite interpolation is a parametric interpolation method, and it is impossible to change the shape of the determined curve after setting parameters. To adjust the shape of the determined curve and optimize the fitting effect, Li et al. put forward a rational Hermite interpolation [18]. Compared with the cubic Hermite interpolation, a shape controlling parameter is used in the rational Hermite interpolation, and the shape controlling parameter can control the shape of the interpolation curve, which further improves the curve fitting effect. Therefore, combining with the advantages of rational Hermite interpolation and ITD, a rational Hermite interpolation - local characteristic-scale decomposition (RHLCD) method is proposed. In RHLCD, when the rational Hermite interpolation is adopted to obtain the envelope signal, the shape controlling parameter could be varied in the sifting process, and the ideal single component signals can be obtained.

For fault condition monitoring, pattern recognition is another crucial step in fault diagnosis [19]. Neural network and support vector machine [20], [21] are frequently-used pattern recognition methods, and the classification effect can often be guaranteed. However, some shortcomings in these two classifications are difficult to overcome [22], [23], such as the choice of parameters or kernel function, and the recognition result is greatly affected by the subjectivity. In addition, it is especially noteworthy that the inherent connections among the extracted features are ignored in aforementioned pattern recognition methods. However, in the extracted features of mechanical vibration signals, there are certain internal relations among the features, and the internal relations between different systems and categories (the same system under different working conditions) are obviously different. Targeting at the inherent relationship among features, Raghuraj et al. put forward variable predictive mode based class discriminate (VPMCD) [24], [25], and VPMCD has been introduced to some research fields, such as biology and machinery [26], [27]. The core of VPMCD is that the best mathematical prediction model is established and chosen through minimum error square and the mutual interrelationship between the features, and then pattern recognition is completed. Among them, the VPMCD method contains four kinds of mathematical models: L (Linear), LI (Linear and Interaction), Q (Quadratic) and QL (Quadratic and Interaction). The four models mentioned are agent models for the real relationship of features, and the optimal model for pattern recognition is chosen. However, the best model is selected in accordance with a single condition and it has a greater chance of the recognition results at the same time. Based on this, a fusion variable predictive model based class discriminate method (FVPMCD) is put forward in this paper, which applies the probability statistics to VPMCD, and the discriminant result is no longer recognized by a single mode. First, four common models are used to recognize a sample and the recognition results of each model are satiated. Then the probability of each state recognition is calculated. Finally, the largest recognition probability of state is chosen to recognize category. When the two or more series have the same probability, the best prediction model of all models is chosen to further identify.

In conclusion, a novel roller bearing fault on-line condition monitoring method based on RHLCD and FVPMCD is put forward. Firstly, the vibration signals in various states are decomposed into several RISCs by RHLCD. Secondly, the features are extracted to construct feature vectors for all RISCs. Finally, these features are used as input vectors for FVPMCD classifier. Thus, this study proposes an efficient way to utilize the benefit of proposed method process to handle the complexity of vibration signals for the application of mechanical system health condition monitoring.

The content of this paper can be composed of the following sections. In section II, A theory of RHLCD algorithm is proposed. In section III, the FVPMCD algorithm is given and the corresponding condition monitoring method is proposed. The proposed method is applied to the fault diagnosis of roller bearing in section V. Finally, the conclusions are drawn in section VI.

II. LOCAL CHARACTERISTIC-SCALE DECOMPOSITION METHOD BASED ON RATIONAL HERMITE INTERPOLATION

A. RATIONAL HERMITE INTERPOLATION METHOD

The cubic Hermite interpolation is a curve structure interpolation method and widely used in engineering. Compared with cubic spline interpolation, cubic Hermite interpolation is applied to fit the local extrema, and it can guarantee the continuity and smoothness of successive points. Meanwhile, this method has an excellent characteristic of shape preservation and is superior to the analysis of strong impact non-stationary signals. In addition, the problems of owe envelope and over envelope are avoided. However, when the interpolation conditions are determined, the curve is also determined. Although the local feature of the waveform can be changed during the sifting process, the cubic Hermite interpolation cannot adaptively control the shape of the curve.

Therefore, the rational Hermite interpolation is introduced to fit envelope curves between extrema. Herein, the shape controlling parameter is introduced to adjust the curve. By adjusting the shape controlling parameter, the approximation fitting effect can be further improved and the effective signal decomposition can be realized. Scholars have proposed many rational Hermite basic functions, but the parameterized rational Hermite basis function is optimal. This function with parameters makes the structure simpler and the calculation faster. Therefore, when rational Hermite interpolation is used to fit the envelope signal, the parameter λ could be varied. The functions of rational Hermite interpolation are as follows:

$$\begin{aligned} F_i(t) &= 1 + (\lambda_i - 3)t^2 - (2\lambda_i - 2)t^3 + \lambda_i t^4 \\ F_{i+1}(t) &= -(\lambda_i - 3)t^2 + (2\lambda_i - 2)t^3 - \lambda_i t^4 \\ G_i(t) &= t + (\lambda_i - 2)t^2 - (2\lambda_i - 1)t^3 + \lambda_i t^4 \\ G_{i+1}(t) &= -(\lambda_i + 1)t^2 + (2\lambda_i + 1)t^3 - \lambda_i t^4 \end{aligned} \tag{1}$$

where, $F_i(t), F_{i+1}(t), G_i(t), G_{i+1}(t)$ are basic functions of rational Hermite interpolation, λ_i is the real number.

The calculation shows that the basic functions satisfy following property:

$$\begin{aligned} &F_i(0) = F_{i+1}(1) = 1, F_i(1) = F_{i+1}(0) = 0, \\ &F_i'(0) = F_i'(1) = F_{i+1}'(1) = F_{i+1}'(0) = 0, \\ &G_i(0) = G_i(1) = G_{i+1}(1) = G_{i+1}(0) = 0, \\ &G_i'(0) = G_{i+1}'(1) = 1, G_i'(1) = G_{i+1}'(0) = 0, \end{aligned} \tag{2}$$

And $F_i(t) + F_{i+1}(t) = 1, G_i(t) = -G_{i+1}(1-t)$

From Formula (2), the rational Hermite interpolation revert to the cubic Hermite interpolation when $\lambda_i = 0$. Therefore, the rational quartic polynomials can be used as a generalization of the cubic Hermite interpolation. In addition, the defined basic function has some advantages, such as simple structure, high computational efficiency and reliable outcomes. Firstly, the shapes of the envelope signals are progressively changed when λ varies. Secondly, if the cube Hermite has a good effect, the rational Hermite also has a good effect in the parameter setting range. Lastly, the problems of over and undershoot would be solved effectively by setting a proper λ value. Herein, the shape controlling parameter determining criterion is introduced in the literature [18].

B. THE RHLCD METHOD

Although some defects of EMD and LMD are overcome in the ITD, the baseline signal in ITD method is obtained by linear transformation on the structure of the signal itself, which would make the waveform produce burr and distortion, and significant signal distortion begins with the second component (namely energy leakage). In addition, ITD method does not explain the physical significance of the algorithm itself and PRC. Therefore, the orthogonality between components will be inevitably affected, and the accuracy of the decomposition result is affected directly. LCD method can effectively overcome the above shortcomings of ITD by using cubic spline interpolation, but it has the continuity of the second derivative in the nodes and has a good effect on smoothing the signal. For strong non-stationary signals, the over-envelope and owe envelope phenomenon will occur, which will lead to the signal waveform distorted.

Therefore, combining with the advantages of Rational Hermite interpolation and ITD, the envelope signals can be obtained by using rational Hermite interpolation, and the energy leakage does not appear, and the continuity and smoothness of the decomposed components are better in the decomposed components. In addition, the application of Rational Hermite interpolation and cubic spline interpolation has a certain similarity, and the physical meaning of the algorithm itself and its components are elaborated theoretically by LCD method. From the idea of LCD, the conditions of defined single component signal can be introduced in the paper. Therefore, based on the physical significance of the algorithm itself and the elaborated mono-component, the rational intrinsic scale component (RISC) could be firstly defined, which would allow instantaneous frequency to have the physical significance. The RISC definition satisfies the two conditions:

(1) For the data set, the marks of any two adjacent extrema are mutually different.

(2) For the data set, the extrema are $X_k, k = 1, 2, \ldots, M$ with their respective corresponding moments $\tau_k, k = 1, 2, \cdots, M$. The section of line formed by connecting any two maximum (minimum) extrema (τ_k, X_k), (τ_{k+2}, X_{k+2}) is between them. Therefore, we can obtain the corresponding moment τ_{k+1} of the maximum (minimum) extrema, and the function value is set to $A_{k+1} = X_k + (\frac{\tau_{k+1}-\tau_k}{\tau_{k+2}-\tau_k})(X_{k+2} - X_k)$, of which the ratio to the relative maximum (minimum) extrema X_{k+1} remains unchanged, satisfying the formula $\frac{A_2}{X_2} = \cdots = \frac{A_{k+1}}{X_{k+1}} = \cdots \mu$.

These two conditions ensure that there is a single mode between any two adjacent extrema of RISC, and the local curve (curve between extrema and adjacent zero point) approximate to the standard sine curve, so the instantaneous frequency has physical significance. The RHLCD algorithm assumes that any complex signal consists of different RISCs, and there is independence between any two RISCs, so that any complex signal can be decomposed into several RISCs, and the detailed steps can be expressed as follows:

Step 1: Set the extrema $X_k(k = 1, 2, \cdots, M)$ while the corresponding moments are $\tau_k(k = 1, 2, \cdots, M)$. Meanwhile, the appropriate parameter a is selected and the baseline control points L_k are calculated. Then change the parameters with the certain length in the range, and get the best baseline signal by rational Hermite interpolation for all L_k.

$$L_k = a\left[x_{k-1} + (\frac{\tau_k - \tau_{k-1}}{\tau_{k+1} - \tau_{k-1}})(x_{k+1} - x_{k-1})\right] + (1-a)x_k \tag{3}$$

Step 2: Subtract baseline L_1 from the signal $x(t)$ and get P_1. Ideally, P_1 is a RISC, which is the first decomposition component. Herein, the ideal RISC should satisfy the condition that L_{k+1} equals zero. Practically, the variation Δ can be set and the iterative is ended when $|L_{k+1}| \leq \Delta$.

Step 3: If P_1 does not meet the conditions of RISC, P_1 should be used as the original signal. Then the P_1 is introduced into steps 1 and 2, and the k times are recycled to obtain P_k. Therefore, P_k is the first component ($RISC_1$).

Step 4: Separate the $RISC_1$ from $x(t)$ to obtain the signal r_1. Then, r_1 is taken as the original signal to repeat step 1–3. Thus, the $RISC_2$ is obtained which satisfies the conditions of the RISC. Repeat it for n times until r_n becomes a monotonic function, and n components which satisfy the conditions of RISC could be got. Now, $x(t)$ is decomposed into n rational intrinsic scale components (RISCs) and a monotonic function r_n, namely

$$x(t) = \sum_{p=1}^{n} \mathrm{RISC}_p(t) + r_n(t) \tag{4}$$

Similar to EMD, the iterative termination criterion of RISC has a great influence on decomposition effect. Therefore, an appropriate criterion must be chosen to obtain the desired RISC. The standard deviation method and the three-parameter method are two commonly used iterative termination methods, which have been proved to have good application effect [27]. Because the algorithm of standard deviation is independent of definition, three-parameter method is applied to set the variation Δ.

C. SIMULATION ANALYSIS

To verify the decomposition performance of RHLCD method, the simulation signal should be constructed, which can be expressed as:

$$x(t) = \cos(60\pi t + 0.5\sin(30\pi t))(1 + 0.2sin(15\pi t)) + sin(240\pi t) \tag{5}$$

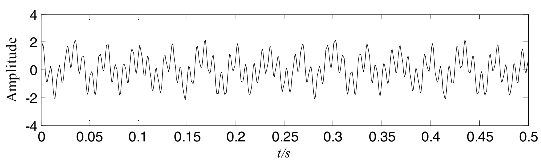

FIGURE 1. The waveform of original simulation signal.

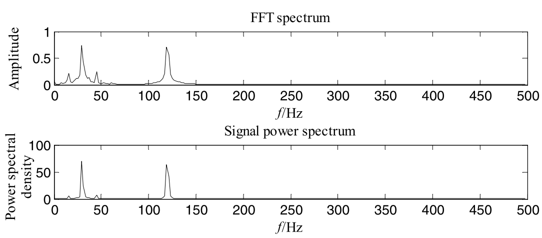

FIGURE 2. The FFT spectrum and power spectral density of simulation signal.

The waveform of $x(t)$ is shown in Figure 1. Figure 2 is the FFT spectrum and power spectrum of $x(t)$, and the frequency of component can be clearly found in Figure 2. Meanwhile, in order to verify the performance of the RHLCD, ITD, LCD and RHLCD are used for decomposition after eliminating end effect respectively. Herein, the mirror symmetry extension method [27] is used to eliminate the influence of the end effect.

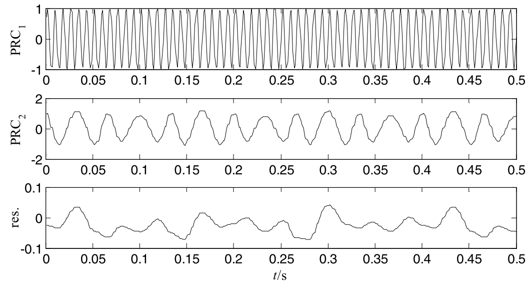

FIGURE 3. The decomposition results of ITD.

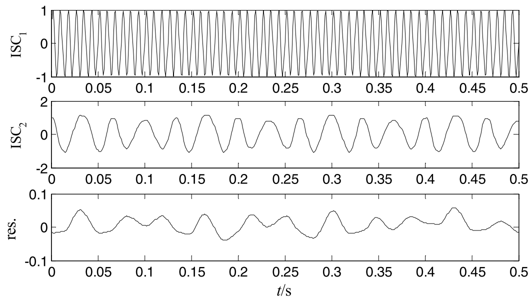

FIGURE 4. The decomposition results of LCD.

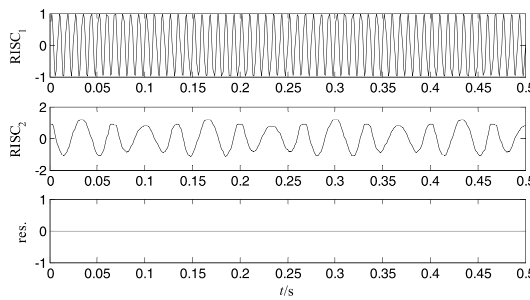

FIGURE 5. The decomposition results of RHLCD.

Firstly, the original signal is processed by a mirror symmetry extension method, and then the extension signal is decomposed by ITD, LCD and RHLCD. Finally, some single component signals are achieved. As it is shown in Figure 3 - Figure 5, some single components can be separated completely by the three methods. In Figure 3, obvious burr phenomenon is shown in the PRCs, which makes PRCs be distorted. LCD method overcomes the burr phenomenon of ITD decomposition, but it still has obvious distortion. In Figure 5, the mono-components of RHLCD show smoothness and avoid burrs, since Rational Hermite interpolation is adopted in RHLCD algorithm instead of linear transformation, and the RISCs have less distortion. Meanwhile, when rational Hermite interpolation is adapted to adjust the envelope signal, the shape controlling parameter could be varied.

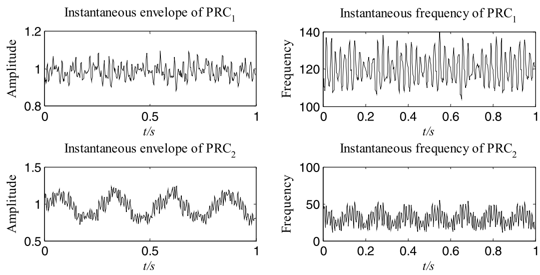

FIGURE 6. The instantaneous envelope amplitude and instantaneous frequency of PRC.

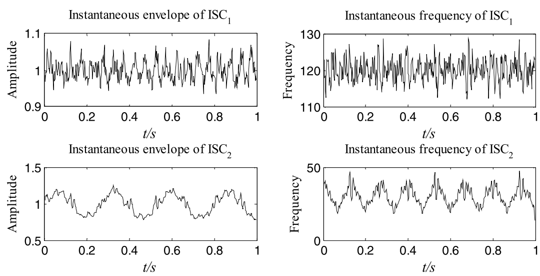

FIGURE 7. The instantaneous envelope amplitude and instantaneous frequency of ISC.

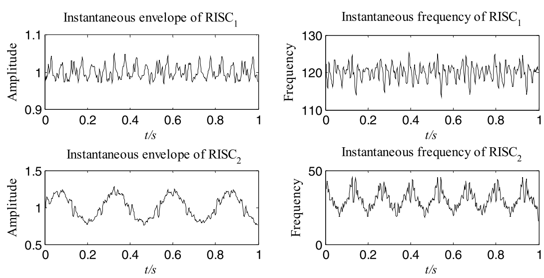

FIGURE 8. The instantaneous envelope amplitude and instantaneous frequency of RISC.

As shown in the above decomposition, the results of RHLCD have obvious advantages. The instantaneous frequency and amplitude of the three components shown in Figures 6 to 8 are used to further verify the superiority of the proposed method. From the Figures 6 to 8, the results of ITD, LCD and RHLCD methods have a great effect on the instantaneous envelope amplitude and instantaneous frequency of the first component, but the effect of RISC$_1$ is much better than PRC$_1$ and ISC$_1$. Compared with the second component, the effect of RISC$_2$ is more accurate than PRC$_2$, which can be found whether it is the instantaneous frequency or the instantaneous envelope amplitude, the less volatile is shown in the waveform while the difference is more obvious. Therefore, the analysis results of the instantaneous frequency and amplitude proves that RHLCD is a more effective and reliable decomposition method than ITD and LCD.

After analyzing the instantaneous envelope amplitude and instantaneous frequency of single component signal, the time-frequency distribution is compared with the above several decomposition methods. Firstly, the decomposition

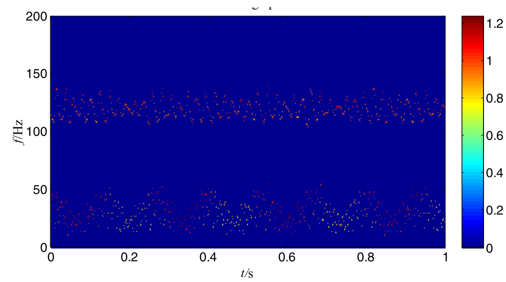

FIGURE 9. The time-frequency distribution with ITD.

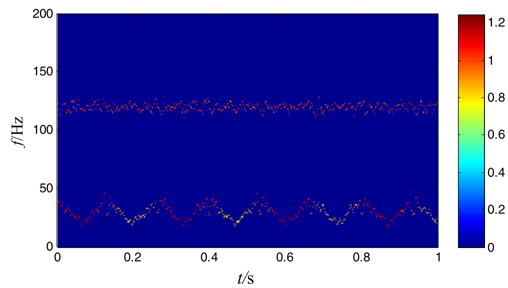

FIGURE 10. The time-frequency distribution with LCD.

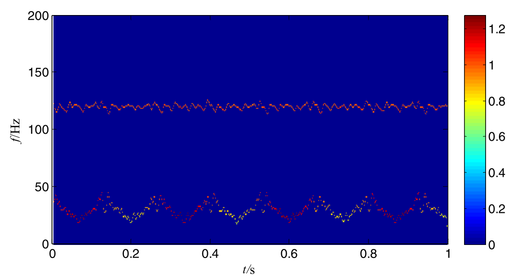

FIGURE 11. The time-frequency distribution with RHLCD.

results through the above several kinds of time-frequency analysis methods are made to achieve Hilbert transform, and then the time-frequency spectra are obtained as shown in Figures 9 and 11. Because the linear transformation is used by ITD decomposition, the obtained time-frequency distribution appears larger distortion. As a result, the original physical meaning of the corresponding spectrum is lost, and instantaneous amplitude and the frequency of original signal changing along with time cannot be reflected accurately. In Figure 10, the time-frequency distribution of LCD improves the larger distortion of ITD, but the high-frequency component still suffers serious distortion. The time-frequency distribution obtained by RHLCD can present the basic information of the original simulation signal well, and there is no large deviation. Therefore, compared with other decomposition methods, RHLCD has obvious advantages.

III. FVPMCD PATTERN RECOGNITION METHOD

In the mechanical condition monitoring, the working states and fault types are often discriminated by extracting the feature of raw vibration signal. However, compared with the feature of normal bearing, that of faulty bearing is not very apparent, the fault type is often contained in the relationship among the features, and one-to-one relationship or one-to-multiple relationship could exist among features. Assuming that a category can be represented by p different features, which is $X = [X_1, X_2 \cdots, X_p]$, and the potential relationship is $X_1 = f(X_2)$ or $X_1 = f(X_2, X_3, \cdots)$. From the above relations, X_1 is not an unrelated independent value with other features, and the different change of X_1 would occur under the influence of other features in different fault categories. In order to recognize fault type of mechanical system, the mathematical models should be established through mutual interrelationship between the features. The variable prediction model VPM_i may be a linear or non-linear regression model (four regression models are proposed in reference [24]). To illustrate the classification problem with p features, the variable X_i can be predicted by any of the four models, which is defined as follows:

$$X_i = f(X_j, b_0, b_j, b_{jj}, b_{jk}) + e \tag{6}$$

where, Formula (6) is the variable prediction model VPM_i of X_i. Herein, X_i is the predicted variable, and $X_j (j \neq i)$ is the predictive variable. e is the prediction error. b_o, b_j, b_{jj} and b_{jk} are the model parameters.

The statistical probability is introduced into the VPMCD in this paper, and the pattern recognition is performed by using four kinds of regression model instead of the single best model, then contingency and one-sidedness are avoided. The probability of each state appears is calculated by using four best models by the statistics, and the maximum probability of state is regarded as a recognition result. Therefore, the contingency and one-sidedness are greatly weakened, which would make the recognition results more objective. The steps of FVPMCD method are as follows:

Step 1: For g sates, n training samples are collected, and the number of samples of each class is $n_1, n_2, \cdots, n_g$. The feature vectors of all samples are extracted as $X = [X_1, X_2, \cdots, X_p]$, and the feature set of all samples can be expressed as $n_1 \times p, n_2 \times p, \cdots, n_g \times p$.

Step 2: Make the type of model $m = 1$ (four kinds of models are signed by 1, 2, 3 and 4 respectively).

Step 3: Let the model order be $r = 1 (0 < r < p)$, k training samples are selected for modeling and analysis. Any feature is chosen as the predictive variable X_i $(i = 1, 2, \cdots, p)$, and $p - 1$ features X_j $(j \neq i)$ are selected as prediction variables. Therefore, C_{p-1}^r VPMs are established for the feature X_i.

Step 4: For each variable prediction model, n_k equations for feature X_i can be established. Meanwhile, the least-squares regression is used to obtain model parameter, and then the prediction variables X_j are back to VPMs to get the predicted value X_{ipred} of the feature X_i.

Step 5: The prediction error sum of squares $SSE_l = \sum_{v=1}^{n_k} \left(X_{iv} - X_{ivpred}\right)^2$ of C_{p-1}^r VPMs are obtained respectively, where $l = 1, 2, \cdots, C_{p-1}^r$, and v is the vth training sample. The VPMs corresponding to the minimum value of SSE_l are selected as the $VPM_i^k (i = 1, 2, \cdots, p)$ of the feature $X_i (i = 1, 2, \cdots, p)$ in the k class training samples, and the corresponding model parameters and variables are retained.

Step 6: Let $k = k + 1$, and repeat step $3 \sim 5$ until $k = g$. Thus, so far, it is the case that the type of regression model is m and the type of correlation model is r, g categories of all the features establishing on VPM_i^k separately, where $k = 1, 2, \cdots, g$ denote different categories, $i = 1, 2, \cdots, p$ denote different features. These variable predictive models compose a VPM matrix whose size is $g \times p$. Then let $r = r+1$ and cycle above steps until $r = p - 1$. Thus $p - 1 VPM$ matrices can be obtained under each model and order. All training samples are taken back to each VPM matrix as test samples for classification test respectively. When the classification accuracy is the highest, the model type and model order corresponding to VPM will be taken as the type and the order of optimal variables prediction model.

Step 7: Then make $m = m + 1$, and cycle steps $2 \sim 6$ until $m = 4$. At the same time, each type of model has a best prediction model. Therefore, the type, order, parameter and variable prediction of four optimal various prediction models of all features are determined under various categories.

Step 8: For test samples, the same features as training samples are extracted $X = [X_1, X_2, \cdots, X_p]$. In order to obtain predicted value, variables prediction models are used to predict features of the test samples, where $k = 1, 2, \cdots, g$ denotes different categories, and $i = 1, 2, \cdots, p$ denotes different characteristics.

Step 9: Under the same category, the prediction error sum of squares values of four optimal various prediction models of all the features $SSE^k = \sum_{i=1}^{p} (X_i - X_{ipred}^k)^2$ are obtained, and the minimum value of SSE^k is used as the discriminant function to classify the test samples. Accordingly, when the prediction error sum of squares values in g class is the lowest, the test samples are identified as kth class. Thus, four kinds of the same or different recognition results of four optimal various prediction models can be obtained. Then the probability of each recognition result appeared is counted, if the probability of recognition results of k type is maximum, the test sample will be identified as the k type eventually.

IV. THE ROLLER BEARING CONDITION MONITORING ALGORITHM BASED ON RHLCD AND FVPMCD

Firstly, the roller bearing vibration signal is decomposed by RHLCD, and several RISCs without end effect are obtained. Then, the feature of each component is extracted and the feature matrix is made up. However, different types of features have a direct influence on the diagnosis results, and the selection of feature is particularly important. Generally, singular values with good diagnostic results are used as fault features to diagnose roller bearing faults. Therefore, the singular value is used for fault diagnosis as the feature. Finally, FVPMCD classification method is used to identify the operation condition and fault type of roller bearing. The main steps of the roller bearing fault diagnosis based on the HRLCD and FVPMCD are as follows:

Step 1: Under a certain speed, four kinds of roller bearing states (normal, inner race fault, outer race fault and ball fault) are sampled in sampling rate f_s, and N groups of samples are collected in each state.

Step 2: The vibration signals are decomposed by RHLCD, and i RISCs are obtained. For each RISC, the singular value is extracted as feature, and each sample can get i features and form feature vectors, so that the $N \times i$ order matrix can be obtained in each state.

Step 3: In each state, N samples are selected as training samples and the remaining $n - N$ samples are selected as test ones. Firstly, the four types of prediction models are established for each state through the FVPMCD training, and then the best model of each type is selected through a certain criterion. Finally, the four best models are used to classify the test sample, and the probability statistics are made to determine the fault types of roller bearing.

FIGURE 12. The experimental platform of roller bearing.

TABLE 1. Experimental parameters of roller bearing.

Speed	Sampling frequency	Motor load	Fault width
900r/min	20480Hz	2Nm	0.3mm

V. APPLICATION

A. CASE#1

The good decomposition performance of RHLCD has been verified by simulation signal and in the following, we apply the proposed RHLCD method to the signal of roller bearing with local fault at outer ring (Anhui University of Technology). Figure 12 is the experimental platform of roller bearing, and SKF6205 type roller bearing is selected. The experimental parameters of roller bearing are shown in Table 1. Based on the parameters, the fault vibration signal of the roller bearing outer ring is collected, and its time domain waveform is shown in Figure 13. From Figure 13, the fault characteristic frequencies of roller bearing with outer ring fault are flooded, and the amplitude modulation information cannot be reflected from time domain waveform. Further, the envelope spectrum is used to reflect the fault feature frequencies of the roller bearing signal, which is shown in Figure 14. From Figure 14, we can find that the outer ring of roller bearing is faulty, but there are more interference frequencies in the envelope spectrum.

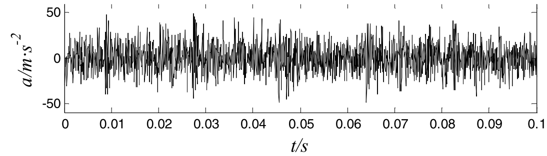

FIGURE 13. The time domain waveform of roller bearing outer ring fault.

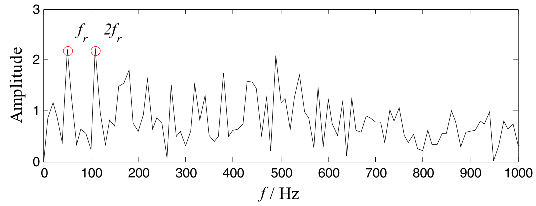

FIGURE 14. The envelope spectrum of roller bearing outer ring fault.

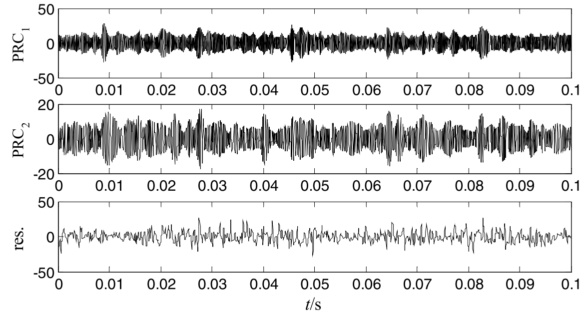

FIGURE 15. The decomposition results of ITD.

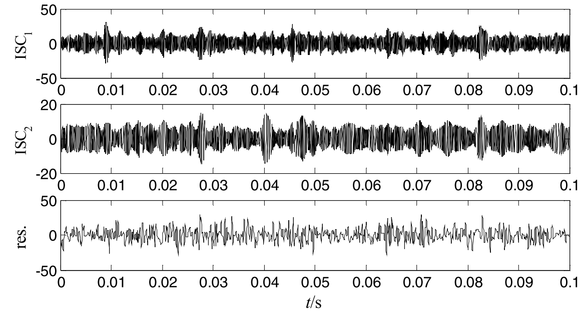

FIGURE 16. The decomposition results of LCD.

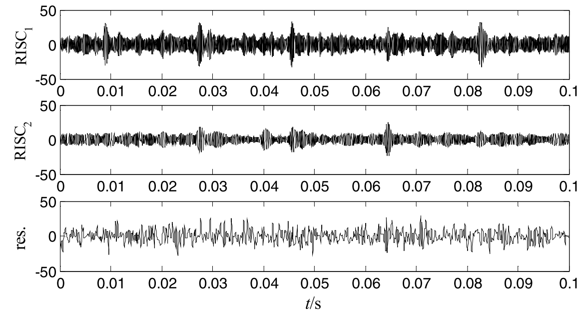

FIGURE 17. The decomposition results of RHLCD.

In order to highlight the superiority of RHLCD method, ITD and LCD methods are used for comparative analysis. The decomposition results are shown in Figures 15 to 17.

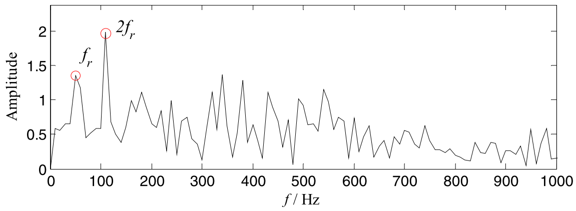

FIGURE 18. The envelope spectrum of first component after ITD.

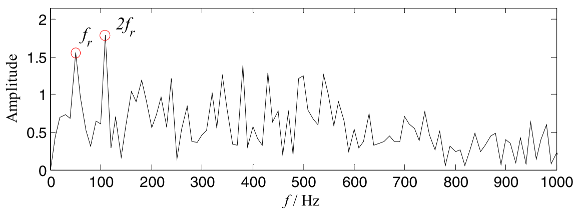

FIGURE 19. The envelope spectrum of first component after LCD.

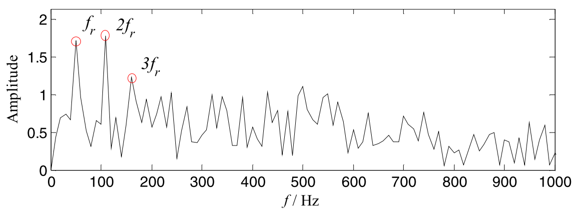

FIGURE 20. The envelope spectrum of first component after RHLCD.

From Figures 15 to 17, compared with ITD and LCD methods, the first decomposition component of RHLCD method has obvious amplitude modulation information. Since the first component has amplitude modulation information, the envelope spectra are obtained for the first decomposition component of above three decomposition methods, which are shown in Figures 18 to 20. As can be seen from Figures 18 to 19, the fault characteristic frequencies are more obvious in the envelope spectrum decomposed by ITD and LCD. However, there are still many interference frequencies in the envelope spectrum. Figure 20 is the envelope spectrum of first component obtained by RHLCD. Compared with the envelope spectrum of ITD and LCD, the fault frequencies obtained by RHLCD are more obvious and the interference frequencies are smaller in the envelope spectrum of the first component after RHLCD than that of ITD and LCD. This is because the control parameter is used to adjust the fitting curve in RHLCD, which makes the signal decomposition better than the original LCD. At the same time, the envelope spectrum obtained can highlight the fault characteristic frequency more clearly.

B. CASE #2

Although RHLCD can realize the fault diagnosis of roller bearings, it cannot complete the intelligent diagnosis of roller bearing. To verify the intelligent diagnosis effectiveness of the proposed FVPMCD method in mechanical fault diagnosis, the actual data of roller bearings in Hunan University

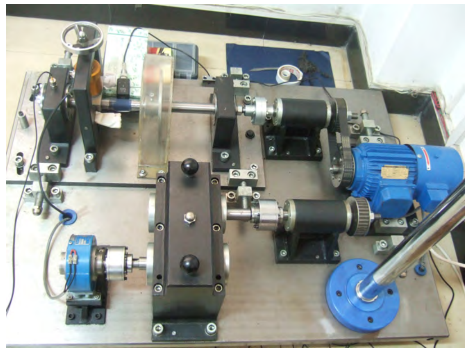

FIGURE 21. Roller bearing fault test rig.

are selected to test the intelligent fault diagnosis effect of RHLCD and FVPMCD. The 6307E deep groove ball bearing is selected to slot on the inner and outer rings of roller bearings respectively. Herein, the groove width is set to 0.15 mm, and the groove depth is set to 0.13 mm. Meanwhile, the experimental conditions are that the rotation speed is kept at 680 r/min and the sampling rate is 4096 Hz. Due to the limitation of experimental conditions, the roller fault cannot be set. Roller bearing fault test rig is shown in Figure 21 (the vibration signal is obtained by the acceleration sensor on the bearing seat.).

The vibration signals of three states (normal, inner fault and outer fault) are collected, and 200 samples are collected in each state. In reality, it is difficult to get abundant known samples, especially the fault samples. Accordingly, random samples of 40 groups of data are regarded as training samples, and the rest of 160 groups are test Samples. The theoretical roller bearing fault vibration signal should have a characteristic of periodic pulse, but the periodic pulse is actually not obvious. Due to the interference of background noise and the limitation of the acquisition condition, the characteristics of fault vibration signal is not obvious than normal state.

Firstly, the original signal for each sample is decomposed by RHLCD and the RISCs without end effect are got. Because the fault information of roller bearing is mainly concentrated on high-frequency band, the first four RISC components would be selected. Therefore, singular values of each component could be calculated, denoting as X_1, X_2, X_3, X_4 respectively, and 200 groups of singular values can be extracted from each kind of data. And then 40 sets of training samples are used to establish the FVPMCD prediction models, and four FVPMCD prediction models are established for each state. Finally, the prediction models are used to identify the test data under four states, and the test samples are identified. In order to illustrate the superiority of FVPMCD method, VPMCD, RBF network, SVM, sparse support vector machine (SSVM) [28] and FVPMCD classifiers are compared. At the same time, in order to highlight the intelligent diagnostic effect of RHLCD and FVPMCD, the combination of LCD and FVPMCD is chosen for comparison. The classification performance comparison results are shown in Table 2 and Table 3.

TABLE 2. The classification performance comparison results of the five classification methods based on LCD.

Classification method	Normal	Inner-race fault	Outer-race fault	Recognition rate
RBF	(158/160) 98.75%	(143/160) 89.38%	(141/160) 88.13%	(442/480) 92.08%
SVM	(159/160) 99.38%	(152/160) 95.00%	(140/160) 87.50%	(449/480) 93.54%
SSVM	(160/160) 100.00%	(153/160) 95.63%	(142/160) 88.75%	(455/480) 94.79%
VPMCD	(160/160) 100.00%	(146/160) 91.95%	(143/160) 89.38%	(449/480) 93.54%
FVPMCD	(160/160) 100.00%	(153/160) 95.63%	(147/160) 91.88%	(460/480) 95.83%

TABLE 3. The classification performance comparison results of the five classification methods based on RHLCD.

Classification method	Normal	Inner-race fault	Outer-race fault	Recognition rate
RBF	(158/160) 98.75%	(145/160) 90.63%	(145/160) 90.63%	(448/480) 93.33%
SVM	(160/160) 100.00%	(150/160) 93.75%	(138/160) 86.25%	(448/480) 93.33%
SSVM	(160/160) 100.00%	(153/160) 95.63%	(144/160) 90.00%	(457/480) 95.21%
VPMCD	(160/160) 100.00%	(146/160) 91.95%	(145/160) 90.63%	(451/480) 93.96%
FVPMCD	(160/160) 100.00%	(153/160) 95.63%	(148/160) 92.50%	(461/480) 96.04%

Table 2 and Table 3 show the recognition rates of the five classification methods, and the classification performance of FVPMCD is better than the other four methods. As for the diagnosis results of the normal state, all the five methods have good recognition performance. In the other states, the classification effect of the four methods are inferior to FVPMCD, because the contingency and one-sidedness are greatly weakened in the FVPMCD, which would make the recognition results more objective. In FVPMCD, four kinds of common models are used to recognize a sample, and the recognition results of each model are satiated. Then, the probability of each state recognition is calculated, and the largest recognition probability of state is chosen to recognize category. Therefore, we use the internal relations between different categories to establish a suitable prediction model and obtain satisfactory recognition results. Meanwhile, the recognition results of five methods after LCD and RHLCD decomposition methods are analyzed respectively. From Table 2 and Table 3, it can be seen that the features obtained by RHLCD have higher recognition performance. In addition, while FVPMCD can accurately recognize the state, part of test samples cannot be recognized by using VPMCD, and the part sample of recognition errors by using VPMCD are listed in Table 4 (1, 2 and 3 represent normal, inner-race fault state and outer-race fault state respectively).

From Table 4, due to some existing reasons, the best selected model may not be the most appropriate model, leading to contingency and one-sidedness of VPMCD recognition results. Based on this, four kinds of models are used to identify in FVPMCD, and not all of the four models can be identified accurately. Therefore, the statistical probability is introduced to fuse several recognition results, making recognition results right maximally.

In addition, in order to eliminate the accidental factors, three kinds of test methods (Re-Substitution (RS) method, K-fold cross-validation (K-CV) method and Jack-knife (JK) method) are adapted to verify the effect of FVPMCD in this paper. The RS method can be used to verify self-compatibility of test algorithm, and the K-CV can test the objective recognition rate of the classification algorithm. JK test is performed for a machine learning algorithm, which can reflect the generalization ability. Therefore, the recognition performance of FVPMCD is analyzed by the above test methods and it is also compared with VPMCD in the recognition rate. 200 groups of data are all verified, and the results are shown in Table 5.

Table 5 shows the discrimination results of two classification methods under the three tests, and the recognition performance of FVPMCD is better than that of the VPMCD by three test methods. The classification performance of VPMCD is inferior to FVPMCD because the single model is used in the VPMCD, and the multi-model fusion technology

TABLE 4. The part sample of recognition errors by using two methods.

True state	Recognition state of VPMCD optimal prediction model	Recognition state of FVPMCD prediction model				
		L	LI	Q	QI	Final recognition state
1	2	1	1	2	1	1
1	2	1	1	2	1	1
2	3	2	2	2	3	2
2	3	2	2	2	3	2
3	1	3	3	3	1	3
3	2	3	3	3	2	3

TABLE 5. The recognition performance comparison of VPMCD and improved FVPMCD under three kinds of test methods.

Recognition method	Normal	Inner-race fault	Out-race fault	Total
VPMCD (RS)	(199/200) 99.50%	(177/200) 88.50%	(174/200) 87.00%	(570/600) 95.50%
FVPMCD (RS)	(200/200)100.00%	(196/200) 98.00%	(189/200)94.50%	(585/600) 97.50%
VPMCD (10- CV)	(195/200)97.50%	(182/200) 91.00%	(188/200)94.00%	(565/600) 94.17%
FVPMCD (10- CV)	(200/200)100.00%	(186/200) 93.00%	(191/200)95.50%	(577/600) 96.17%
VPMCD (JK)	(196/200)98.00%	(187/200) 93.50%	(181/200)90.50%	(564/600) 94.50%
FVPMCD (JK)	(200/200)100.00%	(188/200) 94.00%	(189/200)94.50%	(577/600) 96.17%

(statistical probability) is used in FVPMCD to overcome the shortcomings of single model and weaken the influence of the ''contingency and one-sidedness'' effectively. Therefore, the superiority of the FVPMCD method is confirmed.

In summary, the recognition results of VPMCD and FVPMCD methods are listed in Tables 2 to 4, which prove that FVPMCD has high recognition rate and can accurately judge the state (VPMCD cannot recognize accurately). Meanwhile, it is proved that the signal decomposition by RHLCD has better recognition effect. Table 5 shows that the recognition rate of FVPMCD is much better than the VPMCD method under different test methods. Therefore, the experimental analysis results of roller bearings indicate that the proposed condition monitoring approach can identify states of roller bearing effectively.

VI. CONCLUSION

In view of the shortcomings of previous decomposition methods, a rational Hermite interpolation—local characteristic-scale decomposition (RHLCD) method is put forward, which can effectively decompose arbitrary non-linear or non-stationary signals, and some continuity and smoothness of RISCs are obtained without energy leakage. Moreover, pattern recognition also play an important role in fault diagnosis of roller bearings. VPMCD, as a classification method suitable for non-linear problems, has achieved good classification results in classification problems. However, the best agent model is chosen for pattern recognition in the original VPMCD method, and it has a greater chance of the recognition results by selecting the best model. Meanwhile, the models established by a small number of samples cannot cover the complicated relations among the features. Therefore, based on the relationship among features, and combined with the advantages of VPMCD and probability statistics, a fusion variable predictive model based class discriminate (FVPMCD) method is proposed in this paper. The analysis results show that the proposed method improves the fault diagnosis performance of rolling bearings and provides a new method for condition monitoring of rolling bearings. In addition, the recognition results are obtained directly from the output of the FVPMCD classifiers, and the proposed condition monitoring method provides the possibility to fulfill an automatic health recognition for roller bearing state and could be successfully integrated in industrial equipment for condition monitoring.

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