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A Fault Diagnosis Approach for Rotating Machinery Rotor Parts Based on Equipment Operation Principle and CEEMD

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1. Introduction

In modern industrial production, rotatory machinery is developing towards large, continuous, highly integrated, automated and high power. The complexity of the equipment, the degree of association between individual devices is also increasing. Although modern machinery has greatly improved production efficiency, the maintenance costs have greatly increased, and the loss caused by equipment failure has also skyrocketed [1,2]. Due to the high rotating speed and tremendous momentum of the rotor, the centrifugal force may lead to the loose or flying apart of the rotor parts, which brings a great threat to the operation safety of the equipment. The fault usually causes damage to multi-stage stationary and non-stationary blades or impellers. This type of fault could lead to high maintenance costs and significant economic loss. However, the capture of the early symptoms of rotor faults is relatively difficult and has become a worldwide challenge in the field of prognostics. In order to master the equipment operation status and avoid accidents, advanced condition monitoring and fault diagnosis technologies need to be researched and applied to detect early faults and avoid malignant accidents, and to fundamentally solve the problem of under-maintenance and over-maintenance that often occurs in the current regular maintenance for the rotatory machinery [3].

For the study of condition monitoring and fault diagnosis of rotor components of the large rotating machinery, the method of rotor component condition monitoring is studied from a methodological point of view to obtain the correct sensitive signal; the failure mechanism of rotor components is studied to explore the new method of fault diagnosis feature information extraction to achieve accurate and sufficient fault feature information from the monitoring signal; with the support of the fault case library, the fault information library and the diagnosis knowledge library, the integrated method of multi-physical quantity integrated fault diagnosis based on pattern recognition method is researched to achieve fault identification and decision making [4]. The development of rotor component fault diagnosis technology for rotating machinery is roughly divided into three stages. In the initial stage, the signals generated by the rotor operation are mainly monitored by the ap-plication of detection instruments, the sensors monitor the raw signals, and the display instruments show the time domain signal waveforms and spectrum conversion results, without other analysis functions. In the middle stage, the rotating machinery rotor parts diagnosis technology has been developed into detection instrumentation equipped with simple monitoring signal analysis devices; the instruments used are mainly spectrum analyzers, and manual judgment is required for the diagnostic decision due to poor automation. At present, fault diagnosis systems have been widely used in computer monitoring and intelligent diagnosis systems, using modern devices that can realize real-time monitoring and automatic judgment [5,6].

In this paper, based on the importance of the current research on fault diagnosis methods for rotor components of rotatory machinery, data sources and data forms are introduced in Chapter 2; Chapter 3 is the data processing procedure, in which Section 3.1 introduces the data pre-processing method based on mechanism analysis, Section 3.2 introduces the CEEMD method and presents the results on feature extraction; Chapter 4 presents the analysis and discussion of the results.

2. Introduction of vibration data of rotating machinery

The dataset in this paper is from the prognosis dataset of the rotor parts fly-off from the Industrial Big Data Challenge 2019 (http://www.industrial-bigdata.com).

There are five units' data in the provided dataset, including two failed units (M1 and M2) which are within six months prior to the occurrence of the rotor component dislodgement failure, and the other three units (M3, M4 and M5) which have not experienced such failures at least one year after the data were obtained. Among them, the data of each unit contains five stages, a, b, c, d and e, indicating different times near to the occurrence of the fault, as shown in Table 1. In alphabetical order, "a" indicates that the data is collected near the time of the fault, and "e" indicates that

Table 1

Vibration displacement data

Unit	Near to fault	Fault development			Far from fault
M1	M1a	M1b	M1c	M1d	M1e
M2	M2a	M2b	M2c	M2d	M2e
M3	M3a	M3b	M3c	M3d	M3e
M4	M4a	M4b	M4c	M4d	M4e
M5	M5a	M5b	M5c	M5d	M5e

the data were collected far from the fault occurred. The data in each stage contains radial, axial and custom directions, and hundreds of data are collected in each direction, and 1024 vibration displacement values and corresponding frequency and speed information are obtained in each acquisition.

3. Procedure of data processing

3.1. Data pre-processing based on mechanism analysis

In the processing industry, mechanical equipments are always in operation, and are influenced by external factors, so the direct processing and fault diagnosis of vibration displacement sensor data have certain errors. Through the mechanism analysis, the dimensionless index characteristics are selected as the more suitable parameters to describe the operation of mechanical equipments [7]. Among them, the dimensionless index parameters include the shape indicator, the impulse indicator, the clearance indicator, the crest indicator, the kurtosis indicator, etc., which have the following advantages.

1. The dimensionless indicators fully reflect the fault state.

2. The dimensionless indicators are not affected by the absolute level of the vibration signal.

3. Failures with multiple defects coexisting have an insignificant effect on dimensionless indicators.

4. The working conditions, loads, and rotational speeds have essentially no effect on the dimensionless indicators [8].

According to the form of vibration displacement data, the data categories are roughly divided, namely: M1a-M1d and M2a-M2d are fault data, M1e, M2e, M3, M4 and M5 are normal data. And the common testing direction of each unit is selected in the dataset; six directions such as the joint-end X, the joint-end Y, the non-link-end X, the non-link-end Y, the shaft displacement A and the shaft displacement B are selected for the subsequent study. The characteristic parameters of rotor working conditions for each period of each unit are extracted and counted, and the maximum value of rotor speed and fluctuation amplitude are listed for horizontal and vertical comparison, and the results are shown in Table 2. From Table 2, the following two conclusions can be drawn.

1. The different speed ranges of mechanical equipments of different units indicate that there are differences in the operating conditions.

2. When the same unit of mechanical equipments is in different periods, there are differences in speed.

From this, it is inferred that each unit of equipments may be in different operation stages, which needs to be analyzed by combining characteristic quantities such as frequency and amplitude. From data visualization, i.e., three aspects of the time series data visualization, the frequency

Table 2

Rotor condition data of each unit in each period

	Maximum speed (r/min)	Minimum speed (r/min)	Speed differential (r/min)
M1a	5876	4899	977
M1b	5787	4913	874
M1c	6069	6069	0
M1d	5451	4898	553
M1e	5379	5649	270
M2a	9415	9203	212
M2b	9311	8990	321
M2c	8729	2	8727
M2d	8723	8691	32
M2e	2	2	0
M3a	994	993	1
M3b	995	994	1
M3c	994	993	1
M3d	995	994	1
M3e	995	994	1
M4a	5579	5556	23
M4b	5592	5496	96
M4c	5583	5570	13
M4d	5601	5595	6
M4e	5590	5564	26
M5a	2970	2970	0
M5b	2970	2970	0
M5c	2970	2970	0
M5d	2970	2970	0
M5e	2970	2970	0

domain data visualization, and the speed-frequency visualization, all the sampled data are depicted in the same figure to synthesize the equipment operation dynamic graph, as shown in Fig. 1.

From Fig. 1, a, the amplitude fluctuates within a small range with 0 as the reference, and the rotational speed is approximately 3300 r/min, so this stage is classified as the rotational speed sensing fault stage. From Fig. 1, b, the amplitude still fluctuates within a small range with 0 as the reference, and there is still a certain rotational speed, so this stage is classified as the sensing zero drift stage. From Fig. 1, c, the amplitude gradually increases from 0, and the rotational speed also gradually increases from 0 to 9000 r/min, so this stage is the start-up stage. And from Fig. 1, d, the amplitude basically stabilizes, and the speed and frequency also fluctuate normally within a certain range, so this stage is the effective smooth stage.

The analysis can divide each unit into three stages, i.e., the shutdown stage, the start-up stage, and the running stage. Vibration displacement data can be divided into four data types, i.e., the speed sensing fault, the sensing zero drift, the start-up phase, and the effective smooth phase. The specific data distribution is shown in Table 3. Among them, Type 1 represents the tacho-sensor fault stage, Type 2 represents the sensing zero-point drift stage, Type 3 represents the start-up stage, Type 4 represents the effective smooth stage, and "-" represents the marginal invalid data. The data from the effective smooth stage are selected for subsequent extraction of information from dimensionless statistical feature values as new feature covariates to expand the data dimension and prevent the occurrence of overfitting.

3.2. Data processing based on CEEMD

By adding N pairs of noise of the opposite sign to

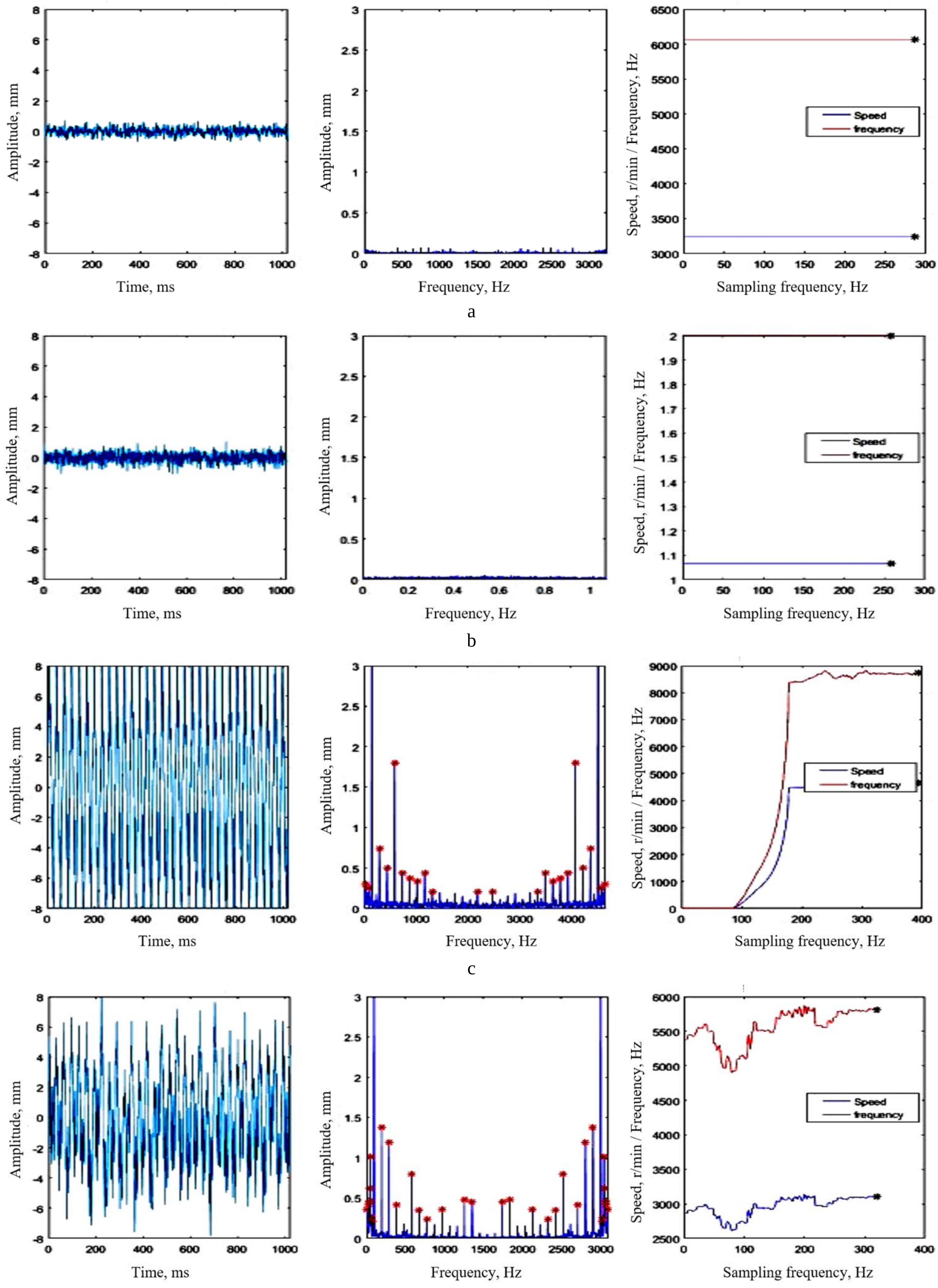


Fig. 1 Data visualization of running condition: a – speed sensor failure, b – sensor zero drift, c – startup stage, b – effective stabilization stage

Table 3

The distribution of vibration displacement data

No.	Stage	Joint-end X	Joint-end Y	Non-link-end X	Non-link-end Y	Shaft A	Shaft B
1	M1a	4	4	4	4	4	4
2	M1b	4	4	4	4	4	4
3	M1c	1	1	1	1	1	1
4	M1d	4	4	4	4	4	4
5	M1e	-	-	-	-	-	-
6	M2a	4	4	4	4	4	4
7	M2b	4	4	4	4	4	4
8	M2c	3	3	3	3	3	3
9	M2d	4	4	4	4	4	4
10	M2e	2	2	2	2	2	2
11	M3a	4	4	4	4	4	4
12	M3b	4	4	4	4	4	4
13	M3c	-	-	-	-	-	-
14	M3d	4	4	4	4	4	4
15	M3e	-	-	-	-	-	-
16	M4a	4	4	4	4	4	4
17	M4b	4	4	4	4	4	4
18	M4c	4	4	4	4	4	4
19	M4d	4	4	4	4	4	4
20	M4e	-	-	-	-	-	-
21	M5a	1	1	1	1	1	1
22	M5b	1	1	1	1	1	1
23	M5c	1	1	1	1	1	1
24	M5d	1	1	1	1	1	1
25	M5e	1	1	1	1	1	1

the original signal, CEEMD effectively avoids the modal mixing phenomenon and has the advantages of small reconstruction error and high operational efficiency compared to the traditional signal processing method, namely EMD [9].

3.2.1. Fundamentals of EMD and CEEMD

The purpose of EMD is to obtain the IMF, which enables the decomposition of complex signals into a finite number of IMFs, and the individual IMF components of the decomposition contain the local characteristic signals of the original signal at different time scales [10]. EMD enables the non-smooth data to be smoothed, and then Hilbert transform is performed to obtain a time-frequency spectrum to obtain physically meaningful frequencies. It has the advantage that it does not use any defined function as a substrate, but it adaptively generates IMF according to the signal under analysis, and it can be used to analyze nonlinear, non-stationary signal sequences [11]. The EMD algorithm can decompose the original signal continuously to obtain the IMF components under certain conditions [12]. However, IMF decomposition suffers from the phenomenon of modal conflation, i.e., an IMF will contain feature components with different time scales. On the one hand, it is due to the signal itself, and on the other hand, it is the defect of the EMD algorithm itself. Therefore, there is a lot of room for improvement in traditional EMD.

CEEMD adds a set of standard white noise signals with the same amplitude and 180° phase difference to the original signal decomposition, and then performs EMD decomposition of the signal, and sums the modal components of different groups of white noise and calculates their average values, using the result as the new modal components. The efficiency of the signal decomposition calculation has improved [13]. Specific steps are as follows.

1. A pair of standard white noises with the same amplitude and 180° phase difference is added to the original signal $X(t)$ to obtain two new signals $x_1(t)$, $x_2(t)$.

2. EMD decomposition is performed on $x_1(t)$ and $x_2(t)$, each signal is decomposed to obtain a set of modal components, the average value of each set of modal components is calculated to obtain IMF1 and IMF2, and then the average value is solved to obtain the final IMF components.

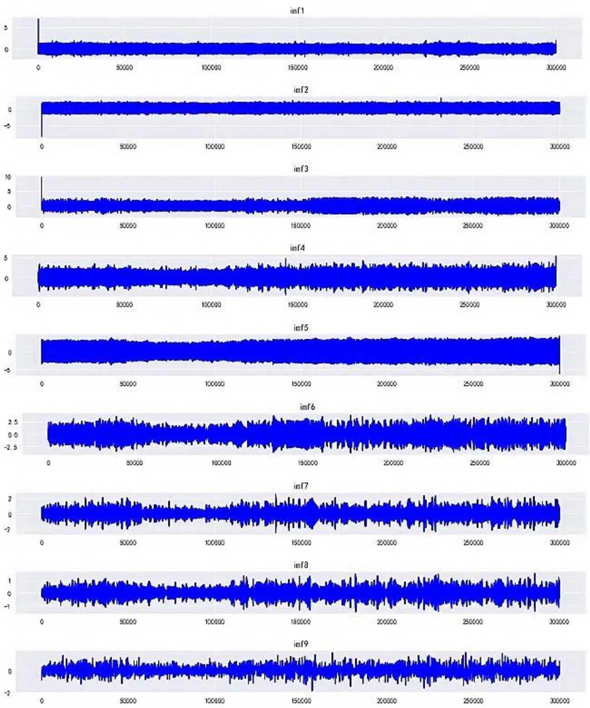
3.2.2. Vibration displacement data processing methods based on EMD and CEEMD

The vibration displacement data of the above effective smooth-running stage are selected, processed by EMD and CEEMD respectively, and the corresponding IMFs and residual component images are plotted. In this paper, the data on the X-direction of the joint end of the rotating machinery M1-M5 are selected for the presentation of the results, as shown in Fig. 2.

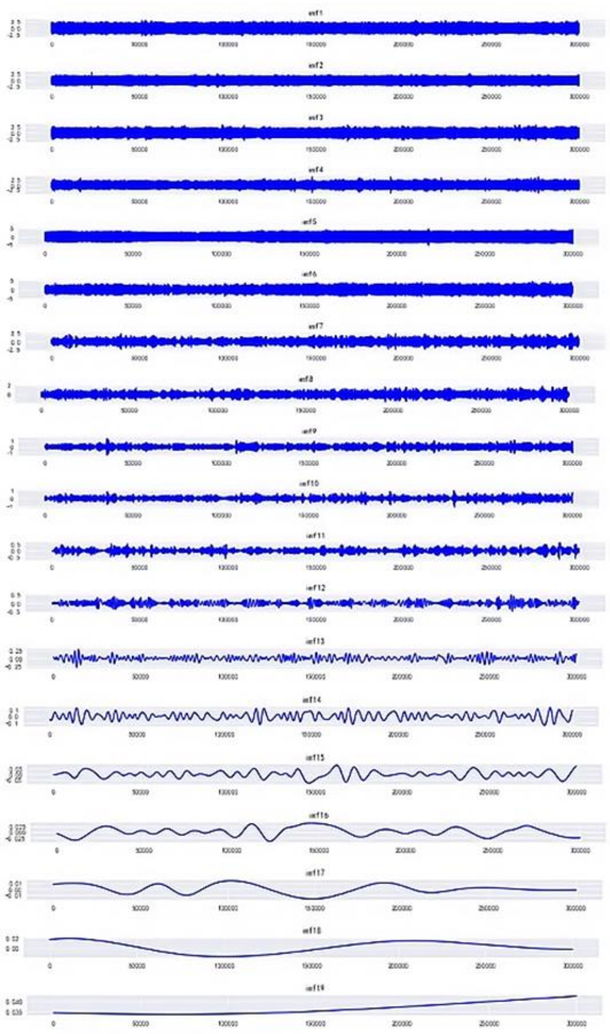
From Fig. 2, it can be obtained that IMF components obtained from the decomposition of the CEEMD method are clearer and more intuitive than those obtained from the decomposition of the EMD method, which decomposes complex data into simpler directions and facilitates the extraction of data information. Therefore, the CEEMD method is selected for data processing. After that, the correlation heatmap of IMF is used to extract the dimensionless statistical characteristics of the first three components with larger correlation coefficients, so as to expand the data dimension and subsequently put them into the machine learning model for training and classification discrimination.

3.2.3. IMF component correlation determination and data feature extraction

The dataset of rotor vibration displacement contains information that is not relevant to the normal operation



a



b

Fig. 2 Processing results for first 30-week data in the Joint-end X direction: a – EMD processing results, b – CEEMD processing results

of the rotor. In order to reduce the redundancy of data and avoid the interference of redundant information, it is necessary to remove false IMF components and extract feature vectors that are relevant to the normal operation of the mechanical equipment rotor, which are usually taken by the methods of principal component analysis [14] and Shannon entropy method. In this paper, the correlation coefficient method is used to remove the redundant components, which are visually represented by the correlation heatmap [15].

The sequence x and y correlation coefficients are calculated as follows.

$$P_{xy} = \frac{cov(x, y)}{(\sqrt{D(x)}\sqrt{D(y)})}, \tag{1}$$

where: P_{xy} is the correlation coefficient, cov(x, y) is the covariance of x and y, and $D(x)$ and $D(y)$ are the variances of x and y respectively. The closer the correlation coefficient P_{xy} is to 1, the larger the correlation; the closer the correlation coefficient is to 0, the smaller the correlation. The heatmap of the correlation of IMF components is shown in Fig. 3.

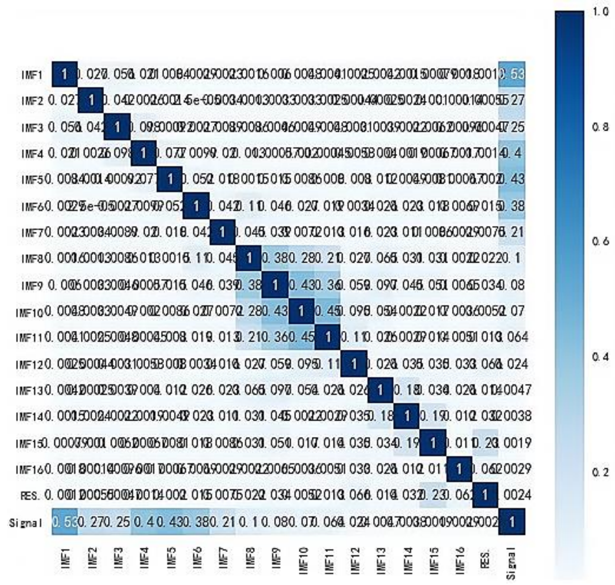


Fig. 3 IMF component correlation heatmap

From Fig. 3, the colors from dark to light represent the correlation of the components with the original signal from high to low, respectively. The top 3 feature components with higher correlations are selected to extract their dimensionless statistical feature indicators, namely: the shape indicator, the impulse indicator, the clearance indicator, the crest indicator, the kurtosis indicator and the skewness indicator, respectively, to expand the original data dimension, add labels and then put into the machine learning model for classification training.

3.2.4. Comparative analysis for EMD and CEEMD

EMD can handle nonlinear and non-smooth signals adaptively, with a high signal-to-noise ratio and good time-frequency focus. However, there are problems with under-envelope or over-envelope, and modal aliasing during IMF decomposition; while CEEMD uses a relatively small number of integrated averaging times by adding N pairs of noise of the opposite sign, and the spectral leakage problem and modal aliasing effect are weakened, while saving computation time and the computational efficiency is improved. Therefore, this paper adopts the CEEMD method to analyze and process the vibration displacement data of rotating machinery.

3.3. Construction and evaluation of machine learning models

3.3.1. Introduction to principle of support vector machine classification model

Support Vector Machines (SVM) is a classification model whose basic model is an interval-maximizing linear classifier defined on a feature space, the interval maximization distinguishes it from a perceptron; SVM also introduces kernel functions, which make it a substantially nonlinear classifier [16]. The learning strategy of SVM is interval maximization [17], which can be formalized as a problem of solving convex quadratic programming, which is also equivalent to the problem of minimizing the loss function of a regularized hinge. The learning algorithm of SVM is an optimization algorithm for solving convex quadratic programming [18].

For a nonlinear classification problem in the input space, it can be transformed into a linear classification problem in some dimensional feature space [19] by a nonlinear transformation to learn a linear SVM in a high-dimensional feature space. Since both the objective function and the classification decision function in a pairwise problem learned by a linear SVM involve only the inner product between instances [20], it is not necessary to explicitly specify the nonlinear transformation, but to replace the inner product among them with a kernel function. The kernel function is expressed as the inner product between two instances via a nonlinear transformation [21]. Specifically, $K(x, z)$ is a function, or positive definite kernel, implying the existence of a mapping $\phi(x)$ from the input space to the feature space [22], for any x, z in the input space, with

$$K(x,z)=\phi(x)\bullet\phi(z) \quad (2)$$

In the pairwise problem learned by the linear SVM, the kernel function $K(x, z)$ is used to replace the inner product and the solution is obtained as a nonlinear SVM [23] as follows.

$$f(x)=\operatorname{sign}\left(\sum_{i=1}^{N}\alpha_i^* y_i K(x,x_i)+b^*\right) \quad (3)$$

3.3.2. Introduction of classification model result evaluation index

When performing SVM classification tests, it is difficult to get a correct assessment of the algorithm's effectiveness by using only one metric for the processing of the results. Therefore, four metrics such as accuracy, precision, recall and F1-score are generally used [24]. The definitions are as follows.

1. True Positive (TP): True positive measures the extent to which the model correctly predicts the positive class. That is, the model predicts that the instance is positive, and the instance is actually positive.

2. True Negative (TN): True negatives are the outcomes that the model correctly predicts as negative.

3. False Positive (FP): False positives occur when the model predicts that an instance belongs to a class that it actually does not. False positives can be problematic because they can lead to incorrect decision-making.

4. False Negative (FN): A false negative occurs when a model predicts an instance as negative when it is actually positive.

In the confusion matrix of Table 4, 1 represents the positive class and 0 represents the negative class [25].

Table 4

Confusion matrix

		Predicted		Total
		1	0	
Actual	1	TP	FN	Actual Positive
	0	FP	TN	Actual Negative
Total		Predicted Positive	Predicted Negative	TP + FN + FP + TN

In this paper, the accuracy score, the precision score, the recall score and the F1-score are used to describe the results of the proposed approach.

1. The accuracy score is a machine learning classification model performance metric that is defined as the ratio of true positives and true negatives to all positive and negative observations. In other words, accuracy tells us how often we can expect our machine learning model will correctly predict an outcome out of the total number of times it made predictions.

$$Accuracy=(TP+TN)/(TP+FN+TN+FP) \quad (4)$$

2. The precision score is a useful measure of the success of prediction when the classes are very imbalanced. Mathematically, it represents the ratio of true positive to the sum of true positive and false positive.

$$Precision=TP/(FP+TP) \quad (5)$$

3. The recall score is often used in conjunction with other performance metrics, such as precision and accuracy, to get a complete picture of the model's performance. Mathematically, it represents the ratio of true positive to the sum of true positive and false negative.

$$Recall=TP/(FN+TP) \quad (6)$$

4. The F_1-score represents the model score as a function of precision and recall score. Mathematically, it can be represented as a harmonic mean of precision and recall score.

$$F_1=2\times Precision\times Recall/(Precision+Recall) \quad (7)$$

3.3.3. Results of SVM model for vibration displacement data

The vibration displacement data of the effective smooth phase after the EMD decomposition process mentioned above were put into the SVM classification model for training and prediction, and the results were evaluated using the evaluation indexes mentioned above, as shown in Table 5. The vibration displacement data of the effective smooth phase after the above CEEMD decomposition process were put into the SVM classification model for training and prediction, and the results were evaluated using the above evaluation indexes, as shown in Table 6.

Table 5

EMD results of SVM model

Evaluation index	Value
Accuracy score	0.974256
Precision score	0.969450
Recall score	0.992451
F1-score	0.980814

Table 6

CEEMD results of SVM model

Evaluation index	Value
Accuracy score	0.981634
Precision score	0.978564
Recall score	0.993102
F1-score	0.985780

From Table 5 and Table 6, we can be obtained the CEEMD method can better comply with the trend of vibration data. It can be more accurate to make classification judgment, for rotor fault detection of rotating machinery, with high practical application value [26].

3.4. Discussion

In this paper, the effectiveness of the proposed method is verified on a turbine data set. However, the CEEMD method is suitable for fault diagnosis of a wider range of rotating machinery equipment with nonlinear and non-stationary characteristics. Therefore, we expect to apply this method to more fault diagnosis applications of rotating machinery equipment in the future.

4. Conclusion

In this paper, the vibration displacement data of the rotor part of large rotating machinery are selected and studied in two aspects: data pre-processing and vibration signal processing. The data pre-processing part is combined with the operation mechanism of rotating machinery to select effective data for feature extraction; the vibration signal processing part adopts the comparison method of EMD and CEEMD to decompose the intrinsic mode function. By extracting the information of dimensionless statistical indicators in the components, CEEMD can determine whether the mechanical rotor malfunctions in operation more accurately, which is of high application value for rotor component fault diagnosis of rotating machinery.

The classification model composed by SVM in this paper has high accuracy and good generalization ability to determine and classify mechanical rotor faults, which can effectively determine the occurrence of faults in mechanical rotors. Compared with other classification models, SVM has higher accuracy, which makes it more suitable for the practical application of rotor fault diagnosis in mechanical equipments.

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A FAULT DIAGNOSIS APPROACH FOR ROTATING MACHINERY ROTOR PARTS BASED ON EQUIPMENT OPERATION PRINCIPLE AND CEEMD

S u m m a r y

Aiming at the problem of fault diagnosis of rotor parts of large rotating machines, a fault diagnosis approach based on the equipment operation principle and the Complementary Ensemble Empirical Mode De-composition (CEEMD) method is proposed. First, the vibration displacement data of the rotor in each direction during the operation of rotating mechanical equipments are pre-processed; then, the vibration data, in the effective smooth operation stage based on the equipment operation principle, are selected for Empirical Mode Decomposition (EMD) and CEEMD analysis methods to evaluate the equipment operation status; finally, vibration data are analyzed to extract dimensionless statistical indicators by the Intrinsic Mode Function (IMF) component. The effectiveness of the proposed approach is verified by the prognostic dataset of rotor parts fly-off in the Industrial Big Data Challenge 2019. From the experimental result, fault diagnosis of rotor components of large rotating machinery is successfully realized by establishing the proposed approach.

Keywords: fault diagnosis, rotor parts fly-off, equipment operation principle, Complementary Ensemble Empirical Mode Decomposition (CEEMD), Industrial Big Data Challenge 2019.

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