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Research on Fault Diagnosis Method of Rotating Machinery Based on Extreme Learning Machine

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***Abstract*—The space station has gradually entered the world. It is equipped with centrifuges for variable gravity experiments. The stagnation of centrifuge may lead to the increase of motor current, which may lead to fire. Vibration signal of centrifuge is unstable and asymmetric. Secondly, the first order modal functions are used to obtain the spectrum by Fourier transform, and the information entropy intrinsic mode function of the spectrum is calculated. At the same time, information entropy is used as a fault feature and dimensionality reduction. Finally, the fault features are trained by the extreme learning machine method, and the actual data acquisition training method is used.**

Keywords—information entropy; intrinsic mode function; extreme learning machine

I. INTRODUCTION

Centrifuge in scientific experiments you, but the ground centrifuge failure will not cause a particularly serious impact. The fire severity in closed space is much higher than that in open space. And the space station is affected by microgravity, which leads to the spread of flames everywhere, and the centrifuge jamming leads to serious safety accidents. In addition, the failure of centrifuge will lead to the outflow of working substance, which will enter the electronic equipment under microgravity conditions and cause short-circuit fire. Therefore, fault monitoring is very important.

The basic process of vibration measurement is: the sensor converts the motion of the vibration body into electrical signal, but because the output signal (voltage or current) of the sensor is too weak to be directly used as the input of the display and analysis instrument, it needs to be amplified by the signal conditioner; because the sensor outputs analog signal, while the modern signal analysis and processing instrument and storage unit are all used. Digital integrated circuit or computer, so it is necessary to use data acquisition device to convert analog signal into discrete digital signal for processing; and in order to avoid the digital signal after sampling may incorrectly reflect the original continuous signal, it is necessary to filter the signal before sampling the continuous signal and remove the high-frequency component of the signal. In addition, if the measured object is a mechanical component or structure without vibration excitation source, it is necessary to use the exciter to excite the measured object to produce vibration. The measured vibration signals are processed by digital signal analyzer or computer to obtain useful results such as power spectrum, structural modal parameters and frequency response function..

In this paper, The dimension-reduced information entropy is taken as the fault feature of centrifuge. Finally, the fault feature is divided into two groups. One group is trained by the extreme learning machine method, the other group is tested by data. The results show that the method has higher accuracy and faster calculation speed.

II. FAULT FEATURE EXTRACTION AND ELM PRINCIPLE

A. *Vibration Signal Extraction*

First, EMD is a special breakthrough in linear and steady state graphic analysis based on Fourier transform. This method does not assume, but decomposes the signal according to the characteristics of the signal target, which is essentially different from the Fourier decomposition and wavelet decomposition methods of prior harmonic basis function and wavelet basis function.

It is suitable for the analysis of non -stationary and non -stationary signal sequences and has a high ratio of signal to marine noise, atmosphere, sky observation data and seismic analysis, mechanical malfunction diagnosis, mitigation of the identification of a dynamic system with a close frequency and determination of modal parameters for large structures.

Firstly, various noise processes are decomposed repeatedly by EMD, and the sum of average values is calculated, which is defined as $IMF_1$of target signal x.

$$IMF_1 = \frac{1}{I}\sum_{i=1}^{I} E_1(x+\varepsilon_0 w^i) \tag{1}$$

The first order residuals are:

$$r_1 = x - IMF_1 \tag{2}$$

The decomposition target is $r_1 + \varepsilon_1 E_1(w^i) \quad i = 1,...,I$ Define the sum of average value as second IMF

$$IMF_2 = \frac{1}{I}\sum_{i=1}^{I} E_1(r_1 + \varepsilon_1 E_1(w^i)) \tag{3}$$

Through the definition of an emperor function, we can see that each vibration period defined by the zero of the sum has only one vibration mode and no other complex single wave; the narrow-band signal of the function can be lipid-adjusted, may be modulated by frequency and amplitude, or may be unstable; the signal modulated by frequency or amplitude itself can also become a mode function.

$$\frac{1}{I}\sum_{i=1}^{I} E_1(r_k + \varepsilon_k E_k(w^i)) = IMF_{k+1} \tag{4}$$

Continue to decompose until the residual meets the agreed requirements.

B. *Short-time Fourier Transform*

Short-time Fourier transform is a general signal processing tool in broad sense. This method defines useful time and frequency distributions by specifying the complex magnitude and magnitude of any signal varying with time and frequency. In fact, the process of calculation is to divide a long time signal region into shorter segments of the same length, and transform each shorter segment with Fourier transform..

$$S(t,\omega) = \left|F(t,\omega)\right|^2 \tag{5}$$

STFT is obtained by short-time Fourier decomposition of the spectrum, So the signal characteristic is centered on T will be displayed in $F(t,\omega)$ [5].

These dynamic rigidity analysis and processing systems will be widely used in the future. They can be used to improve the dynamic response characteristics of automobiles, vehicles, submarines, aircraft, spacecraft, etc.

C. *Extreme Learning Machine*

For N arbitrary distinct, activation function g(x)and standard SLFNs with N hidden nodes are mathematically modeled as

$$\sum_{i=1}^{L}\beta_i g_i(\mathrm{x}_j) = \sum_{i=1}^{L}\beta_i g(\mathrm{w}_i \square \mathrm{x}_j + \mathrm{b}_i) = \mathrm{o}_j \quad j = 1,\ldots,N \tag{6}$$

ELM can obtain depth structure in the form of stack self-encoder. In the process of learning, several hidden layers in the front end of deep ELM use ELM training stack self-encoder to learn the representation of input variables, and in the last hidden layer ELM is used to decode the encoded features.

$$\sum_{j=1}^{L}\left\|o_j - t_j\right\| = 0 \tag{7}$$

There exist β_i, w_i and b_i such that

$$t_j = \sum_{i=1}^{L}\beta_i g(\mathrm{w}_i \square \mathrm{x}_j + \mathrm{b}_i) \quad j = 1,\ldots,N \tag{8}$$

The above equations is

$$H\beta = T \tag{9}$$

Where

$$H\left(W_1,\ldots,W_L,\mathrm{b}_1,\ldots,b_L,X_1,\ldots,X_L\right) = \begin{bmatrix} g\left(W_1 \square X_1 + b_1\right) & \cdots & g\left(W_L \square X_1 + b_L\right) \\ \vdots & \cdots & \vdots \\ g\left(W_1 \square X_N + b_1\right) & \cdots & g\left(W_L \square X_N + b_L\right) \end{bmatrix} \tag{10}$$

$$\mathrm{T} = \begin{bmatrix} T_1^T \\ \vdots \\ T_N^T \end{bmatrix}_{N\times m} \qquad \beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times m} \tag{11}$$

The column of H is the hidden node output with respect to inputs. H is called the hidden layer output matrix of the neural network.

III. Fault Feature Extraction

A. *Acceleration Acquisition*

At present, most of the vibration signals are collected by accelerometers. The output signal of acceleration sensor is processed and output by resonant circuit, the demodulation circuit for cut-off frequency and gain control of the output signal of resonant circuit, and the anti-aliasing filter circuit for processing and output of the output signal of demodulation circuit.

B. *Processing of Vibration Information*

Because of the invention of tracking filter, not only high precision frequency analysis and power spectrum density analysis can be carried out, but also weight skimming can be used for machine impedance analysis. Furthermore, due to the far-reaching time-compressed real-time rate analysis overrun, the previous concept of vibration analysis has been further deepened. Recently, due to the popularity of minicomputers

and the application of Fourier transform, statistical analysis and related analysis techniques have been developed to be able to be processed online in real time. With the development of image and image processing technology, it can be said that the revolution of vibration analysis and data processing has been completed.

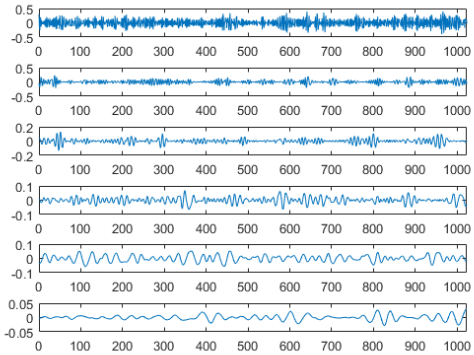

FIGURE I. THE FIRST FEW INTRINSIC MODAL FUNCTIONS

Generally speaking, signal can be expressed as an independent variable by time generalization, and then can be decomposed into various frequency components by Fourier transform. Time and frequency variables are very important variables in the analysis of various stable signals. Frequency domain characteristics of signals are revealed by Fourier transform and various signal domain representations of energy distribution. But Fourier transform is a whole transformation. Signal is characterized by time domain or frequency domain. It is not allowed to analyze the relationship between frequency and time. Real-time. Time-frequency analysis method maps a size field signal to two size time-frequency planes smoothly, reflecting the combination characteristics of unstable signals.

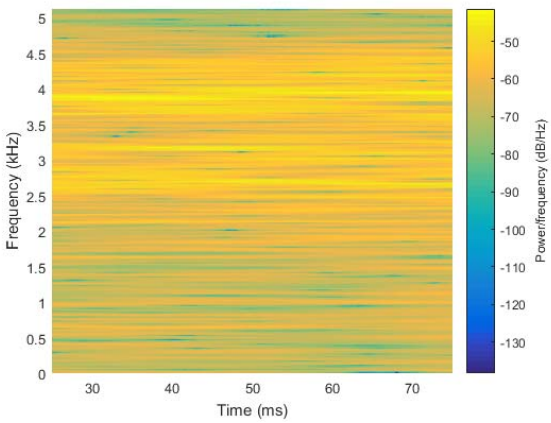

FIGURE II. THE FIRST-ORDER INTRINSIC MODE TIME-FREQUENCY SPECTRUM

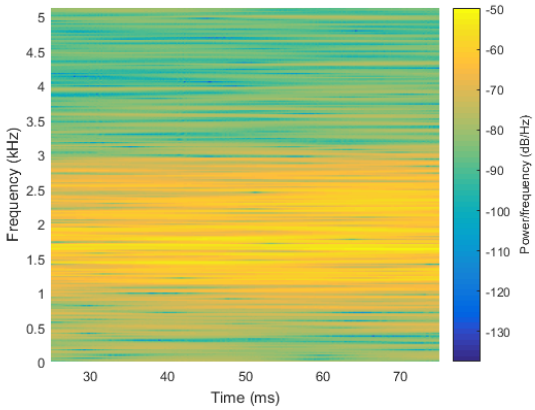

FIGURE III. THE THE FIFTH-ORDER INTRINSIC MODE TIME-FREQUENCY SPECTRUM

IV. REDUCTION DIMENSION AND CLASSIFICATION TRAINING OF FAULT FEATURES

A. *Reducing Dimension by Principal Component Analysis*

The graphics of multidimensional data are the same as the usual water representation. We know that in one edition it is impossible to draw geometric figures at more than three points. The problem of multivariate research can be more than three variables. The problem of graph research is impossible. But after analysis, two main components or two main components can be selected. Samples distributed to the second level can generally be determined according to the principal plane. In the image, each sample can distribute one of the two principal components smoothly. By looking directly at the location, classifying and processing the samples, the expected values far away from the samples can be found from the images.

Principle of analysis of the main component: Using an estimate to mitigate the idea (conversion) under the facility to lose some information, many factories are transformed into some unrelated elements, So each main element is a combination of the original variable and each main part is not connected, making it a better part of the main component for The structure of the system and the capture of the subject may provide more than 90. Information on the first variable. By determining the appropriate value, a low -dimensional system can be transformed into a dimensional system, more computational time and time takes longer than usual, Analysis of data analysis suggests that two -dimensional elements can respond to the need to accumulate and easily to suffering in two dimensions.. The scatter clustering graph of two-dimensional features is shown in Fig. 4.

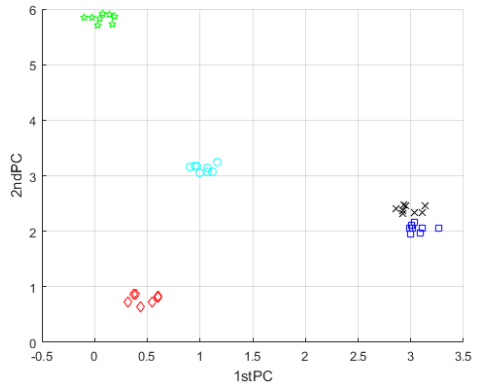

FIGURE IV. THE TIME-FREQUENCY SPECTRUM

B. *Data Training and Testing*

After dimensionality reduction, fault features are divided into two groups of data, namely training data and test data. For various failure modes, four groups of training data and four groups of testing data are used to verify the accuracy of classification. Extreme Learning Machine (ELM) is used as the classification method in this paper. No. 1 represents normal operation, inner ring fault No. 2, outer ring fault No. 3, rolling fault No. 4, mixed fault No. 5. Finally, the fault label identification of test data. The classification results of the test data are shown in Figure 5.

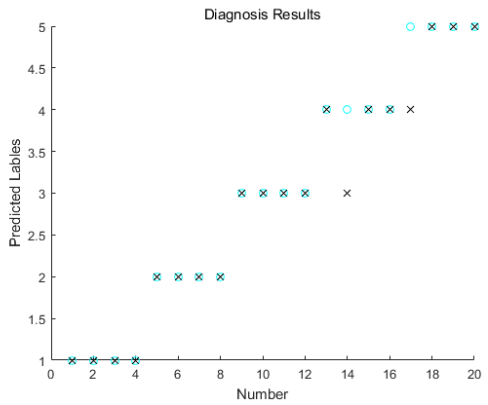

FIGURE V. THE CLASSIFICATION RESULTS OF THE TEST SAMPLES

In this paper, the blue circle represents the training fault category, that is, the actual fault category. The training fault type is consistent with the actual fault type. The black cross sign indicates the type of fault diagnosed by the model. After diagnosis, the fault category label is almost identical with the actual fault mode, with an accuracy of 90%. As shown in Fig. 5, the centrifuge fault diagnosis technology has high accuracy. Because of dimension reduction measures, the calculation amount is small and the classification effect is good. Fault diagnosis and testing technology is oriented to space station electronic equipment, which provides an effective means of diagnosis and testing for all kinds of electronic equipment. On the one hand, it avoids the possible loss caused by ground support delay, improves the emergency handling ability and security assurance; on the other hand, it effectively reduces the demand for the number and weight of diagnostic and testing equipment, and improves the autonomy of space station electronic equipment. At the same time, integrated electronic equipment and simple and portable operation mode reduce the difficulty of operation and further reduce the workload.

V. CONCLUSION

In this paper, sensors are used to collect vibration information of bearings, fault features are extracted through data processing, and ultimately the extreme learning machine is used for training and fit.

REFERENCES

[1] G. B Huang, X. Ding, Optimization method based extreme learning machine for classification [J]. Neurocomputing, 2010, 74 (1-3): 155-163.

[2] Y. Jia, S. Jiann, Complementary ensemble empirical mode decomposition: a novol nosie enhanced data analysis method [J]. Advances in Adaptive Data Analysis, 2010, 2(02).

[3] Y. Xinglin, Fault diagnosis of diesel engine based on CEEMD sample entropy [J]. Internal-combustion engine, 2016(1):46-50.

[4] G. B. Huang, Q. Y. Zhu, Extreme learning machine: Theory and applications [J]. Neurocomputing, 2006, 70(1-3):489-501.

[5] J. Hoffman, N. Merwe, The application of neural networks to vibrational diagnostics for multiple fault conditions [J]. Computer Standards & Interfaces, 2002, 24(2):139-149