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A Fault Diagnosis Method for Satellite Flywheel Bearings Based on 3D Correlation Dimension Clustering Technology

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ABSTRACT Flywheel bearing is a key mechanical part of a satellite. Its health plays an important role in the fatigue life of the satellite. However, it is rather difficult to diagnose the health state of the bearings due to the complex satellite system. This paper attempts to propose a three-direction correlation dimension method to diagnose the bearings of a satellite flywheel at three typical states based on K-medoids clustering technology. A set of spatial spheres representing different bearings are modeled to recognize these three states of the bearings. To avoid misdiagnosis or loss of the bearing state, a twice-cluster scheme is employed. A series of tests is carried out to observe the effectiveness of the proposed method. The result shows that the proposed method is capable of diagnosing the different states of the bearings and its accuracy is higher than 99% at given conditions.

INDEX TERMS Bearing, clustering, correlation dimension, fault diagnosis, K-medoids.

I. INTRODUCTION

Satellite flywheel is a core component of space vehicles in charge of attitude control. It is supported by bearings and provides stable rotating actuation. A flywheel bearing usually consists of one pair of angular contact ball bearings. Sometimes it operates in abnormal conditions, accompanied with strong vibration, rising fiction moment and undesirable high temperature during service. These phenomena may lead to serious damage or even failure of vehicle. In order to prevent a space vehicle from disastrous events, it is essential to monitor the health state of the flywheel bearings.

By far, plenty of researches have been focusing on health monitoring and fault diagnosis of bearings [1]–[4]. Most of them are based on vibration signal processing technology [5], [6] via extracting fault features of bearings from some aspects [7]. Such feature extraction methods include time domain parameter method [6], fast Fourier transform (FFT) [8], envelope spectrum analysis [9], short time Fourier transform [10], Wigner-Ville distribution [11], wavelet transform [12] and empirical mode decomposition (EMD) [13]–[15], etc. They are beneficial to improve the accuracy of fault diagnosis of bearings. The detailed discussion on them can refer to the literatures [16], [17]. However, sometimes these methods do not satisfy the special requirements in applications. For example, Tandon and Nakra [18] conformed that the fault frequency can be directly extracted from the spectrum analysis only when the rolling bearing failure is very serious. Wang and Liang [19] pointed out that the typical envelope spectrum analysis based Hilbert transform needs to choose the center frequency, band of bandpass filter reasonably and suffers to window effect. Rafiee *et al.* [20] denoted that the selection of mother wavelet function, decomposition level of signals and time-frequency resolution of signals are impediments in wavelet transform analysis. Hoseinzadeh *et al.* [21] employed the spline fitting method in EMD to conduct spectrum analysis, but the result is not satisfying and some difficulties like mode mixture and end effect are to be overcome. Aforementioned research denotes that even though some techniques have been proposed in literatures for feature extraction, it is still challenging to own a diagnostic tool for real-world monitoring because of the complexity of bearing vibration response and operating conditions [22]. Moreover, these methods usually require rich knowledge and experience in engineering.

It is well known that the bearing exhibits strong nonlinear dynamic characteristics. Some researchers have devoted to investigating nonlinear feature of vibration signals to diagnose bearing fault. Sadooghi and Khadem [23] discussed the statistical traditional and nonlinear features with support vector machine (SVM) for extracting features. Based on the time-frequency manifold technique, He [24] proposed a nonlinear time-frequency feature for bearing fault pattern classification. Through chaotic theory, Soleimani and Khadem [25] introduced chaotic features such as correlation dimension, the largest Lyapunov exponent and approximate entropy for chaotic vibrations of rolling bearings. Fu [26] pointed out that fractal theory could be used to diagnose bearing failure. Logan and Mathew [27] presented an innovative work on the actual diagnosis of bearing faults by correlation dimension, and they also discussed the calculation of the correlation dimension. Later, they [28] analyzed the optimum values of the time delay embedding and correlation integral parameters based on vibration acceleration data from a rolling element bearing. According to SVM, Yang *et al.* [29] applied combination of the capacity dimension, information dimension and correlation dimension to evaluate fault conditions of rolling bearings. Currently, fractal theory has been widely adopted to describe the nonlinear feature of rolling bearing. However, few literatures have focused on the aerospace rolling bearing with superior property and light load. Since the nonlinear characteristics of the bearings are significantly different from those of ground-mounted bearings, the method of extraction of nonlinear feature for satellite bearings is still worth studying even further.

In order to provide a promising tool to recognize or monitor the states of bearings in satellite flywheels, this paper attempts to propose a three-direction (3D) correlation dimension method based on clustering technology without any information on geometric, physical and kinematic parameters of bearings and flywheels. A series of vibration tests on bearings at three typical states, including normal bearing, a bearing with a fault occurring at outer ring and a bearing with a fault occurring at cage, are carried out. Then the feasibility of one-direction (1D) and 3D correlation dimension analysis based on vibration tests are conducted. Introducing K-medoids clustering into 3D correlation dimension analysis, a model of spatial state spheres representing different states of bearings is established. Furthermore, the model is improved by a proposed twice-clustering approach and verified by the experimental results of satellite flywheels in different states.

II. CHARACTERISTIC ANALYSIS OF SATELLITE BEARING BASED ON CORRELATION DIMENSION

A. BASICS OF CORRELATION DIMENSION

The correlation dimension estimation was put forward by Grassberger and Procaccia [30], so called G-P algorithm. In chaos theory, it is a measure of the dimensionality of the space occupied by a set of random points, often referred to as a type of fractal dimension [31]. It is a popular tool to estimate the distance between all pairs of points in the investigated set. Since the correlation dimension is simple and easy to be implemented, it is commonly used as a parameter to describe the feature of a fractal structure in plenty of applications [32], [33].

A correlation dimension D_2 is defined by [34]

$$D_2 = \lim_{\delta \to 0} \frac{\ln \sum_i P_i^2 (\delta)}{\ln \delta} \tag{1}$$

where δ is a random variable and P_i is a cumulative distribution function with respect to δ, denoting the probability that the trajectory visits the ith element of the partition. Thus the correlation dimension indicates the relative amount of points whose distance is less than δ [35].

A delay embedding attractor is constructed in an embedding space of dimension m with a suitable time delay τ. Then the estimation expression of D_2 in the m-dimensional reconstructed space can be written by

$$D_2 (m) = \lim_{r \to 0} \frac{\partial \ln C_m (r)}{\partial \ln r} \tag{2}$$

with the correlation integral $C_m(r)$ given by

$$C_m (r) = \frac{2}{N_m (N_m - 1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{N_m} H \left(r - r_{i,j}\right) \tag{3}$$

where $H(x)$ is the Heaviside step function

$$\begin{cases} H (x) = 1, & x > 0 \\ H (x) = 0, & x \leq 0 \end{cases} \tag{4}$$

The variable N_m is the number of embedded points in m-dimensional space and r the distance parameter. The variable r_{ij} represents the distance between two reconstructed vectors. It is calculated by using maximum norm [36] in this study.

Correlation dimension calculation highly relies on selection of embedding dimension m and time delay τ [28], [33]. A general way to choose m is the 'saturation' method, in which the appropriate embedding dimension m can be assessed by computing the correlation dimension D_2 for $m \in \{1, 2, \ldots, n\}$ until the variation of D_2 ceases. Another parameter, time delay τ, can be chosen according to autocorrelation function $R_{xx}(t)$ where the function firstly drops to a certain fraction of its initial value, e.g. 1/e (e is the base of the natural logarithm). The details on how to obtain these two parameters can refer to literature [34]. Because the waveform of signals obtained from the antifriction bearing behaves self-similarity in a segment of time history, it is probable to utilize the fractal dimensions for fault diagnosis of bearings [37].

B. GROUND VIBRATION TESTS

In order to find out whether the fractal dimension analysis is applicable to the fault diagnosis of a satellite bearing, a series of tests on flywheel bearings at the real ground operation

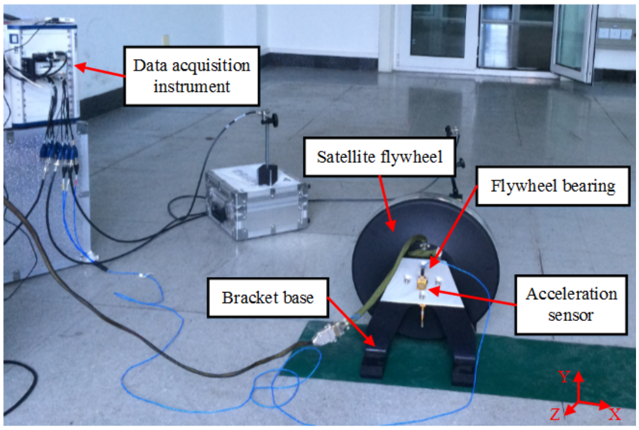

FIGURE 1. Experimental setup of satellite bearing test system.

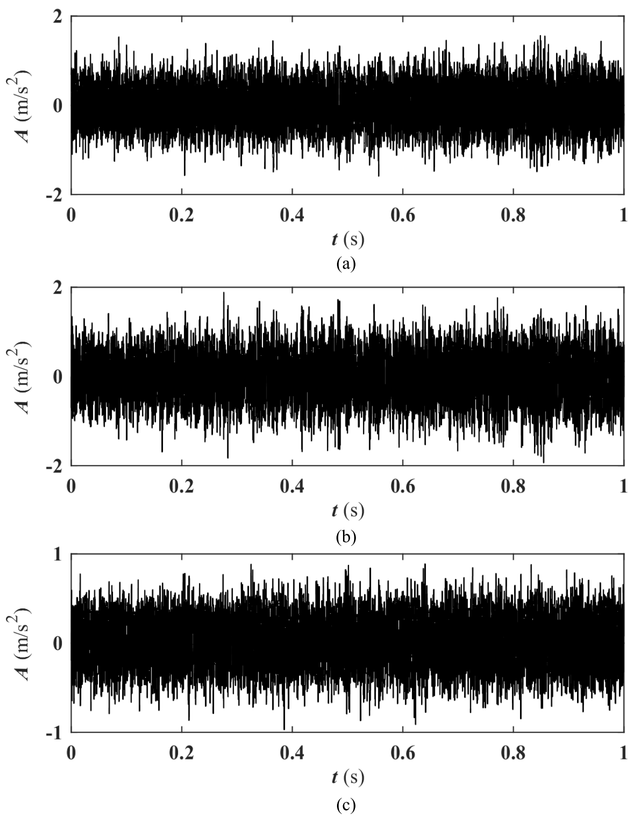

FIGURE 2. The time domain waveforms: (a) x direction; (b) y direction; (c) z direction.

environment are carried out. Fig. 1 shows the experimental setup consisting of one satellite flywheel, four 3D acceleration sensors and one set of data acquisition instrument. Two satellite bearings are installed inside the satellite flywheel and the acceleration sensors are attached on the surface of the bracket nearby the shaft of flywheel and parallel to it. In this figure, the horizontal, vertical and axial directions are represented by x, y and z directions respectively.

Prior to tests, the bearings of 15 flywheels which have already operated for several years are examined carefully.

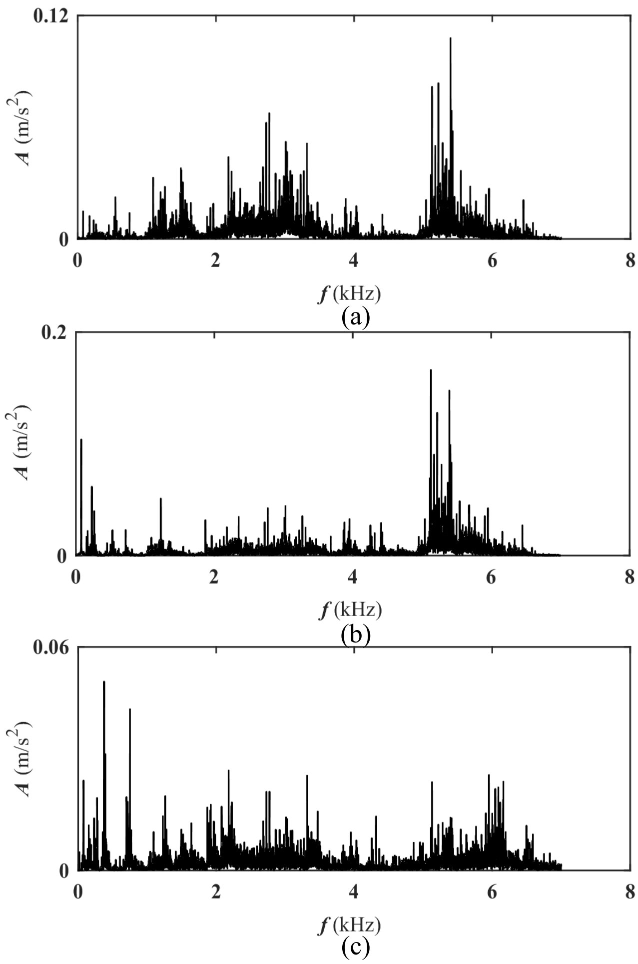

FIGURE 3. The amplitude spectrums: (a) x direction; (b) y direction; (c) z direction.

It is found all bearings are at three states, including normal bearings, the bearings with faults occurring at outer ring and bearings with faults occurring at cage. Thus the target of this study is to provide a reliable way to recognize these three typical states of bearings.

Select three flywheels to conduct the tests. Each of them contains the bearings characterized by one typical state mentioned above. In tests, the 3D vibration signals originating from each bearing sample are picked up to observe whether the distribution of the correlation dimension of bearings at different states has a special rule.

The sampling time of the vibration signals is 20 s. The correlation dimension is calculated at each segment of 0.2 s. Hence totally 100 correlation dimensions are derived for one bearing. To observe the feature of the vibration signal significantly, the waveforms of the signal obtained from a normal bearing sample in 1 s is shown in Fig. 2. And Fig. 3 shows its amplitude spectrum at different directions. It can be seen from these figures that the characteristics of the signal are distinguishing in various directions. Hence the dynamic response in various directions must be different. So do the correlation dimensions.

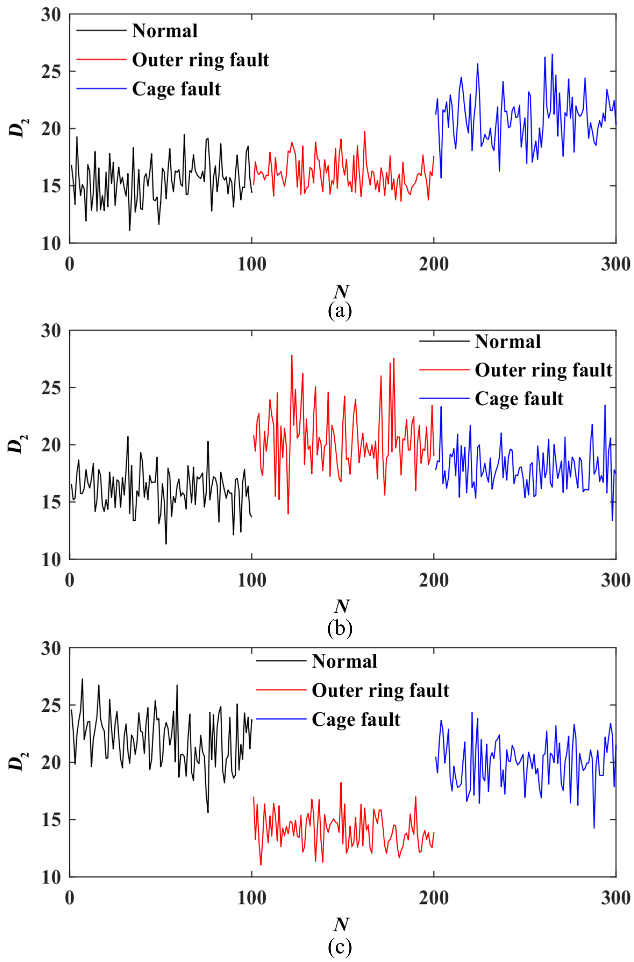

FIGURE 4. Correlation dimensions of tested bearings: (a) x direction; (b) y direction; (c) z direction.

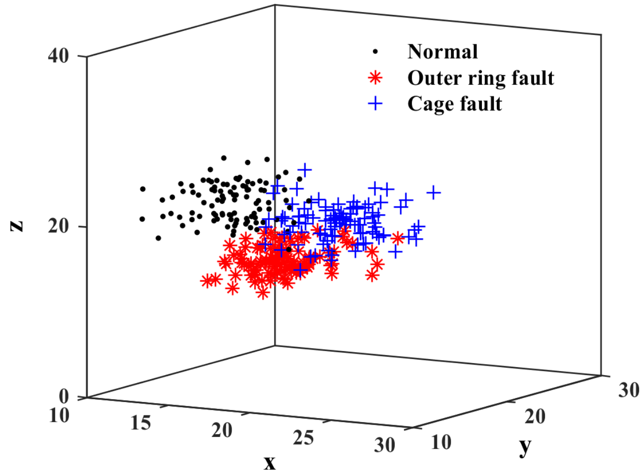

FIGURE 5. Correlation dimensions of vibration signals of bearings at three states.

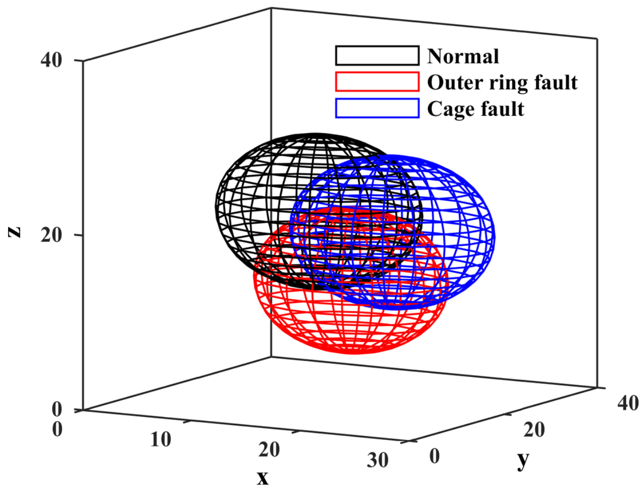

FIGURE 6. Spheres of three bearings built up by using K-medoids method.

C. CHARACTERISTICS OF THE CORRELATION DIMENSION UNDER TYPICAL SURROUNDINGS

Based on (2), correlation dimensions in x, y and z directions can be calculated respectively. In each direction, totally 100 correlation dimensions for one bearing at a certain state are calculated.

Fig. 4 compares the variation trend of the correlation dimension in x, y and z directions, in which the coordinate N represents the number of samples. These samples, numbered from 1 to 100,101 to 200, 201 to 300 in each figure, are those obtained from a normal bearing, the bearing with outer ring fault and the bearing with cage fault respectively. It is shown in the figures that the amplitudes of correlation dimensions of bearings under different states are significantly different and fluctuate heavily at all directions. In addition, the correlation dimensions of one bearing at different states are overlapping and their variations are irregular in different directions. These phenomena might originate from the complex vibration signals. Though the correlation dimension of the vibration signal varies with bearings under different states, it is not probable to recognize the state of a bearing by using the correlation dimension in any direction directly because the overlapping or irregular correlation dimension may easily lead to escape of diagnosis or misdiagnosis.

III. DIAGNOSIS OF BEARING STATE BASED ON 3d CORRELATION DIMENSION CLUSTERING METHOD

A. 3D CORRELATION DIMENSION AND k-MEDOIDS CLUSTERING METHOD

Resulting from characteristic analysis on correlation dimension of bearings, 1D correlation dimension of vibration signals is not applicable to fault diagnosis of bearings. However, the 3D correlation dimensions of bearings at different states are observed to distribute at different spatial regions, as shown in Fig. 5. To take advantage of characteristic of 3D correlation dimension, a scheme based on a clustering method to diagnose the states of bearings is proposed in this study.

Clustering is a way of grouping a set of objects in such a way that objects in the same group, called a cluster, are more similar in some sense to each other than to those in other groups [38]. K-medoids, as one of most popular clustering

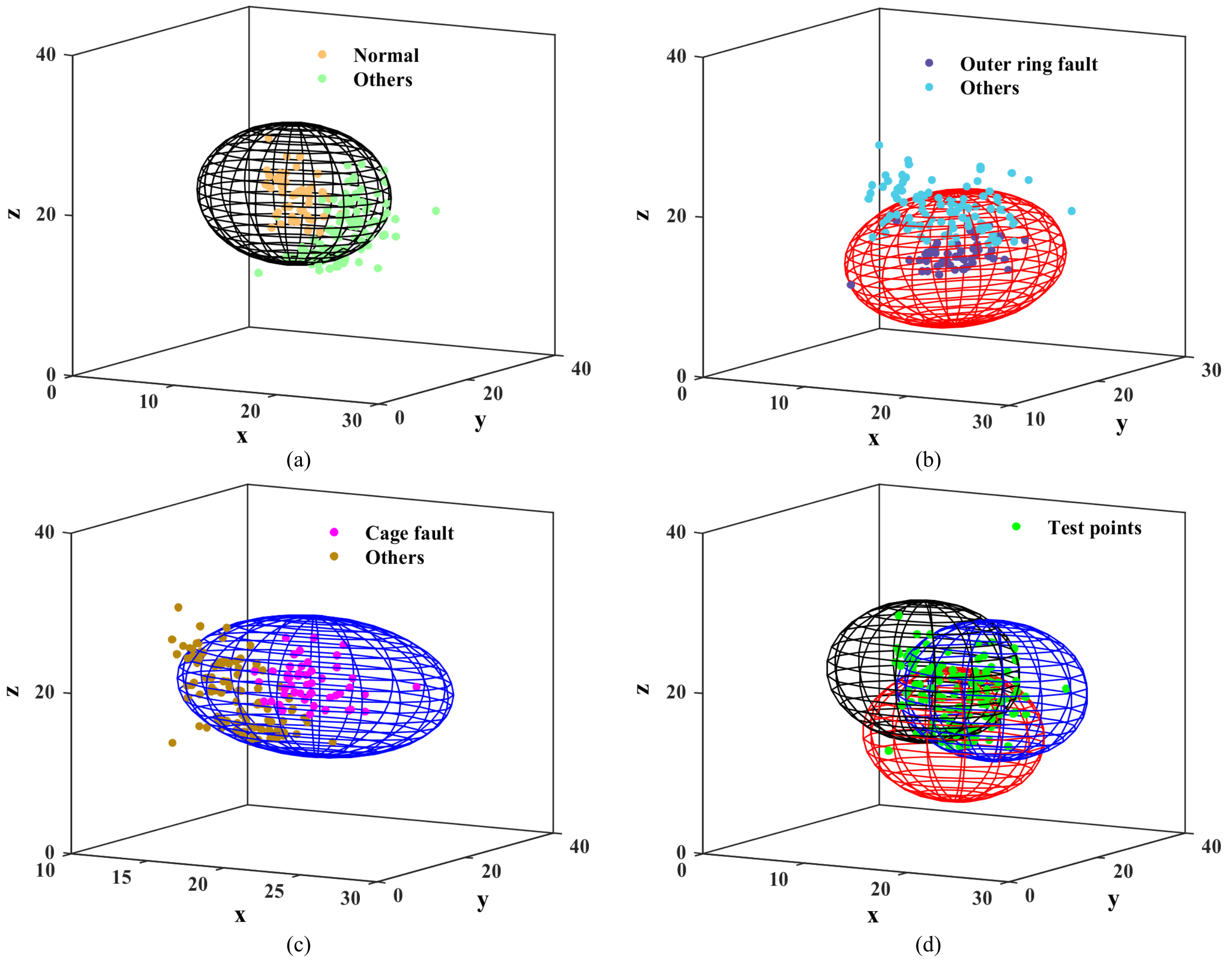

FIGURE 7. **Diagnosis result based on 3D K-medoids method: (a) A normal bearing; (b) A bearing with a fault at outer ring; (c) A bearing with a fault at cage; (d) State spheres.**

algorithms, is a classical partitioning technique of clustering that clusters the data set containing No. a objects into b clusters known a priori [39]. It attempts to minimize the distance between points labeled to be in a cluster and a point designated as the center of that cluster. K-medoids chooses datapoints as centers and works with a generalization of the Manhattan Norm to define distance between datapoints. Since K-medoids is applicable to small sampling clustering analysis and effective to reduce disturbance of noise and outlier [40], [41], it is used in this study to recognize the satellite bearings under different states.

Using K-medoids method, the cluster center of 3D correlation dimensions of bearings at normal state is determined. Taking the maximal Euclidean distance between sampling point and each center as the radius, a sphere centered in cluster center is established. Similarly, two spheres representing the other two states of bearings are obtained. Fig. 6 shows all these three spheres resulting from K-medoids method. The parameters of the clustering spheres are listed in Table 1.

TABLE 1. **Parameters of the spatial state spheres.**

State of bearing	Coordinate of sphere center x	y	z	Radius of sphere
Normal	14.7346	16.1843	22.0015	8.7764
Outer ring fault	15.9678	20.1435	13.6558	8.2493
Cage fault	20.9641	17.3589	20.1670	8.6895

It is shown in Figs. 5 and 6 that 3D correlation dimension is advanced to 1D correlation dimension in fault diagnosis of bearings because the state sphere based on it is capable of recognizing different states of bearings. However, these spheres are spatially overlapped with each other. It means some correlation dimensions are located inside two or more spheres simultaneously.

Carry out the vibration test of Section II (B) again on three states of bearings. Each sample is tested in 10 s and then its

TABLE 2. The independence of parameters of state sphere on different selected items.

State of bearing	Selected number l	Coordinate of sphere center x	y	z	Radius of sphere
Normal	10	14.7346	16.1843	22.0015	3.9374
	20	14.7346	16.1843	22.0015	2.7578
	30	14.7346	16.1843	22.0015	2.7743
Fault in out ring	10	15.9678	20.1435	13.6558	3.3639
	20	15.9678	20.1435	13.6558	2.4469
	30	15.9678	20.1435	13.6558	2.4297
Fault in cage	10	21.2028	17.7672	20.4974	3.5204
	20	20.9641	17.3589	20.1670	2.6591
	30	21.2010	18.6028	20.0319	2.4043

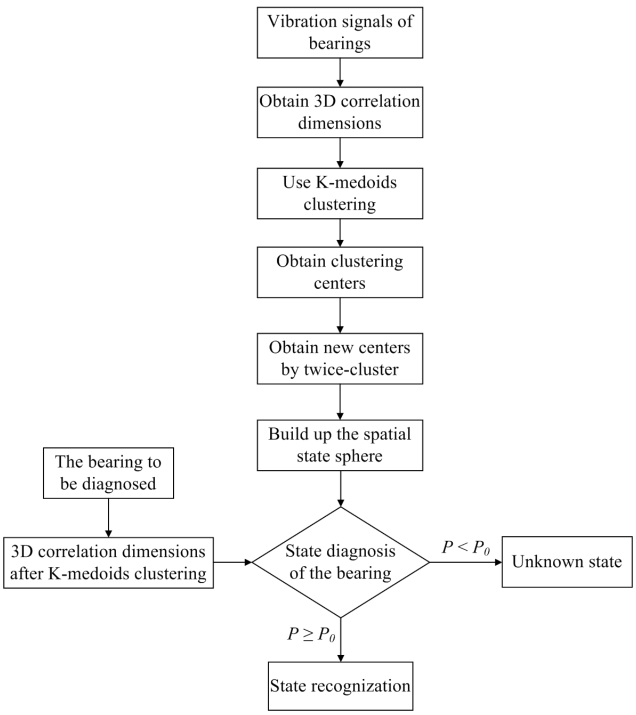

FIGURE 8. Flowchart of fault diagnosis of bearings.

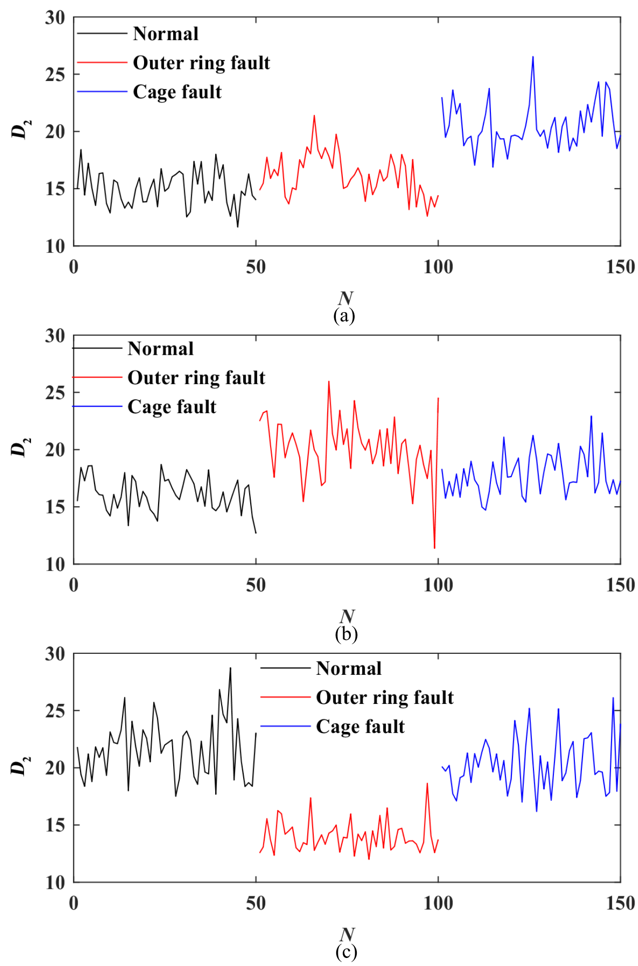

FIGURE 9. Correlation dimensions of three typical states of bearings used for validation: (a) x direction; (b) y direction; (c) z direction.

correlation dimension is calculated at every 0.2 s. As a result, 50 dimensions for each bearing are obtained. Fig. 7 shows the diagnosis result based on the established state spheres. It is seen that the most test data locate inside their corresponding spheres. However, some test data belong to two or more state spheres simultaneously. This phenomenon is the same with the result of Fig. 6. It means current method may lead to misdiagnosis or loss of a fault.

B. IMPROVEMENT OF THE DIAGNOSIS METHOD

It is analyzed from the clustering algorithm that overlapping of the states spheres is probably due to the extra border caused by some outlier when determining the radii of the spheres. In order to reduce the effect of the outliers, this study proposes a method to improve the aforementioned scheme by building up a new spatial state sphere based on the clustering centers. To authors' knowledge, the data during such process may reduce the effect of data fluctuation. A flowchart of the proposed method is shown in Fig. 8 and the detailed procedure on diagnosis of a bearing is described as follows:

(1) Build up the 3D state sphere.

Choose a bearing at a known state. Randomly select l items from any 3D correlation dimension set containing k correlation dimensions to run K-medoids clustering. Repeat it n times, n clustering centers are obtained. Group these clustering centers as a new set to run clustering again, called twice-cluster, the center of these clustering

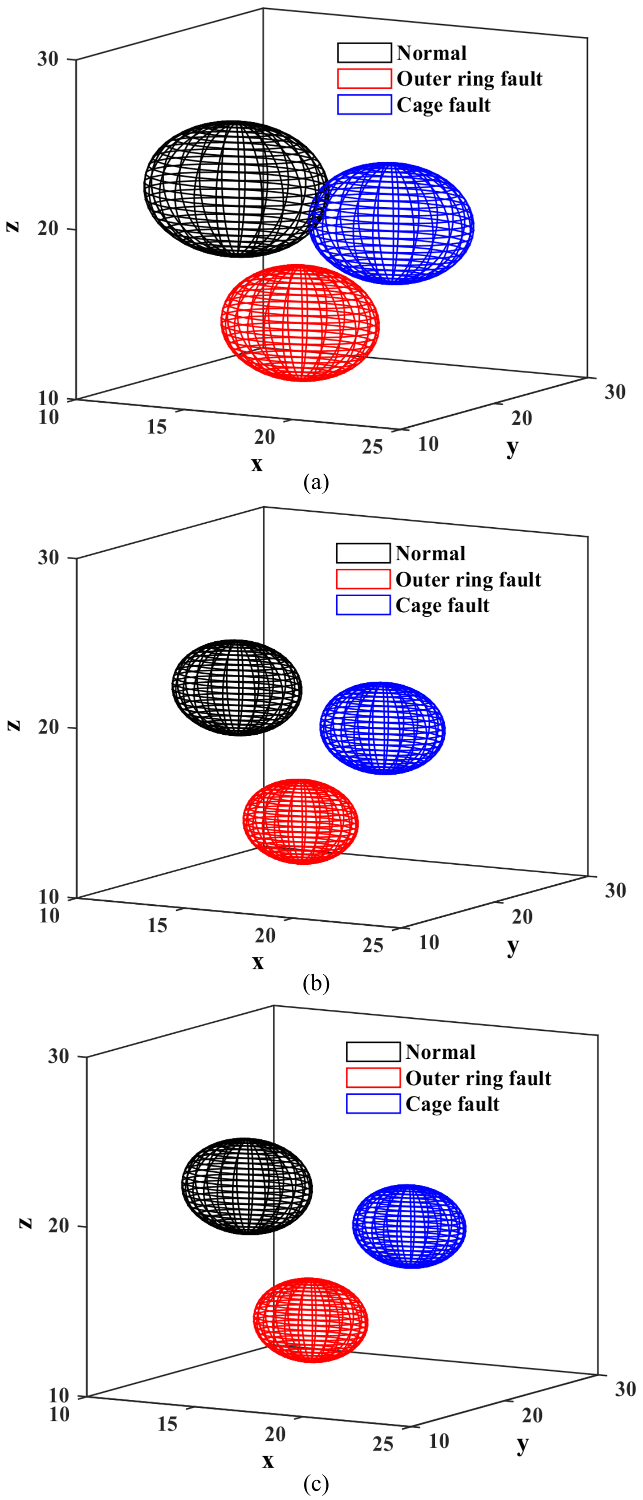

FIGURE 10. **The state spheres at sampling 5000 times: (a) l = 10; (b) l = 20; (c) l = 30.**

centers O is created. Then calculate the Euclidean distance between this center and all clustering centers, and define the maximum one as R. Use the twice-cluster center O as a sphere center and the maximum Euclidean distance R as the radius to build up a 3D sphere. This sphere can be utilized to

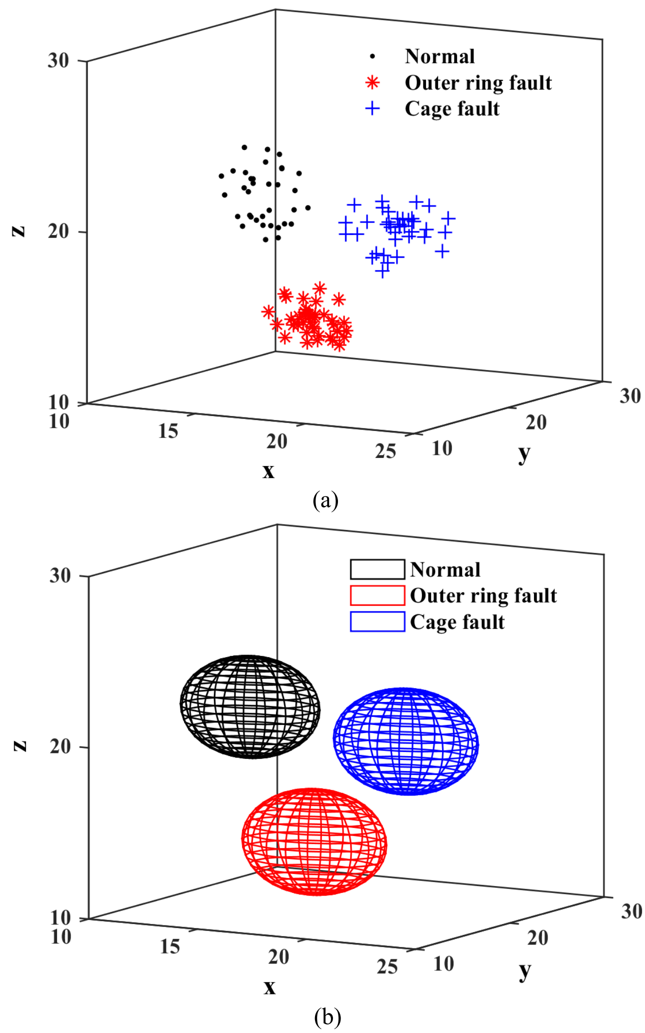

FIGURE 11. **The established spatial state spheres: (a) The 3D correlation dimension distribution; (b) three spatial state spheres.**

represent the state of the satellite bearing. Repeat the same process to build up spheres for other bearings at different states.

(2) Diagnose the state of the bearings

Carry out vibration test for the bearing to be diagnosed. Calculate the correlation dimensions based on its vibration signals and then create a data set containing k correlation dimensions. Run K-medoids cluster n' times to obtain n' clustering centers. If most of these centers, for example 90%, locate in any state sphere built up previously, the state of bearing is identified to be the same with it. Otherwise it is recognized to an unknown state of bearing. In this study, a parameter P is defined to denote the diagnosis accuracy, which is represented by the percentage of real data localized in the state sphere.

IV. EXPERIMENTAL VALIDATION

To evaluate the effectiveness of the proposed method, the independence of the established spatial state sphere on the cluster parameters is checked prior to method validation.

TABLE 3. The independence of parameters of state spheres on different sampling times.

State of bearing	Times of sampling N	Coordinate of sphere center x	y	z	Radius of sphere	Average of radius
Normal	5000	14.7346	16.1843	22.0015	2.7743	2.73
		14.7346	16.1843	22.0015	2.7578	
		14.7346	16.1843	22.0015	2.6511	
	20000	14.7346	16.1843	22.0015	2.9248	2.94
		14.7346	16.1843	22.0015	2.9482	
		14.7346	16.1843	22.0015	2.9351	
	100000	14.7346	16.1843	22.0015	2.9248	2.93
		14.7346	16.1843	22.0015	2.9482	
		14.7346	16.1843	22.0015	2.9248	
Outer ring fault	5000	15.9678	20.1435	13.6558	2.4297	2.71
		15.9678	20.1435	13.6558	2.7612	
		15.9678	20.1435	13.6558	2.9276	
	20000	15.9678	20.1435	13.6558	3.0606	2.98
		15.9678	20.1435	13.6558	3.0606	
		15.9678	20.1435	13.6558	2.8189	
	100000	15.9678	20.1435	13.6558	3.0606	3.08
		15.9678	20.1435	13.6558	3.1286	
		15.9678	20.1435	13.6558	3.0606	
Cage fault	5000	21.2028	17.7672	20.4974	2.7934	2.84
		20.9641	17.3589	20.1670	2.6584	
		21.2028	17.7672	20.4974	3.0640	
	20000	21.4440	17.7141	19.9435	2.9323	2.98
		21.2028	17.7672	20.4974	2.9364	
		21.2028	17.7672	20.4974	3.0640	
	100000	21.2028	17.7672	20.4974	3.0640	3.07
		21.2028	17.7672	20.4974	3.0422	
		20.9641	17.3589	20.1670	3.1071	

The number of correlation dimensions obtained from the previous vibration test is 50 for each state of bearing. Fig. 9 shows the correlation dimensions of three typical states of bearings at x, y and z directions respectively. Randomly select $l = 10$, 20 and 30 items respectively from the 3D correlation dimension sets of different states of bearings and run twice-cluster sampling process $N = 5000$ times to establish state spheres, as shown in Fig. 10. It is seen that the state spheres at condition $l = 10$ are overlapped, but others are not. Table 2 shows the independence of state sphere parameters on selected number l. The coordinates of centers of spheres at different l are almost no change at any certain state of bearing. Though the radius of a sphere is changed with different l, its variation is not monotonic. It is easy to be explained because the proposed method is based on a random sampling calculation, thus the result would heavily rely on the sampling times and the selected items rather than the selected number. Considering the calculation efficiency, the parameter l is assumed by 20 under such condition.

The independence of state sphere on sampling times is analyzed and the comparison result is summarized in Table 3. It can be found the center coordinate of state spheres are almost the same and their radii are not obviously different at sampling times $N = 5000$, 20000 and 100000. It means the sampling time 20000 is large enough to build up a state sphere with acceptable accuracy. At each sampling time, the parameters of a state sphere, including coordinate of center and radius, are calculated three times and the state sphere with the largest radius among them is used in the study because it may include the most data to be diagnosed.

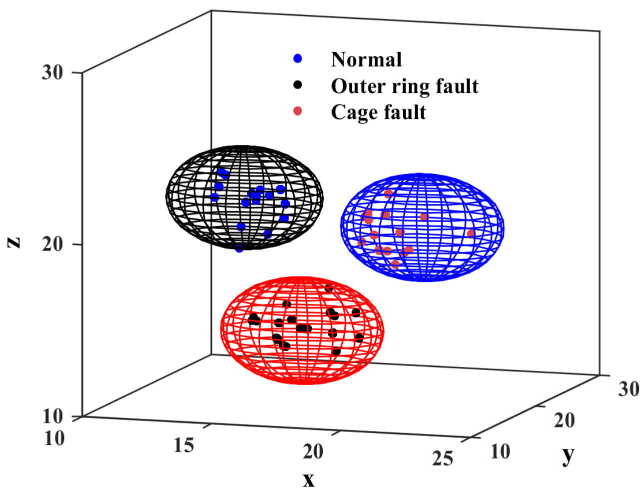

FIGURE 12. The diagnosis of experimental samples.

Fig. 11 shows three spatial state spheres representing different states of bearings under condition of $l = 20$ and sampling times $N = 20000$. It can be seen in this figure that the three spheres are not overlapped with each other by using the proposed method.

Based on the proposed method, the 3D state spheres representing different states of bearings, including normal bearings, bearings with obvious outer ring fault and bearings with

TABLE 4. Diagnosis result by using the general K-medoids and proposed methods.

State of bearings	Accuracy P (%)	
	K-medoids method	Proposed method
Normal	14	99.7
Outer ring fault	46	100
Cage fault	16	99.8

cage fault, are established. Run clustering to all test samples of each bearing to obtain the clustering centers respectively and observed which 3D sphere they localize inside. The test results of three bearings are shown in Fig. 12.

It is seen in Fig. 12 that almost all cluster centers of test samples localize inside the 3D state spheres. Table 4 compares the accuracy of diagnosis result by using the general 3D correlation dimension and the proposed method respectively. It is found in the result the method is much more accurate to diagnose the state of a bearing than the former one. The accuracy is denoted by the percentage of test data inside their corresponding state sphere. Since the state spheres are no longer overlapped, the diagnosis result based on the proposed method may not be associated with misdiagnosis or loss of the fault.

It can be seen that the proposed method is capable of recognizing the typical states of bearings and its accuracy is up to 99%. Fault diagnosis based on the proposed method is easy to be implemented without filtering or going through complex feature extraction procedure, and it need not any geometric, physical and kinematic parameters of bearings and flywheels. These are what it is unique to other conventional fault diagnosis methods such as EMD and FFT.

V. CONCLUSIONS

This paper proposes a 3D correlation dimension method to diagnose three typical states of bearings in a satellite flywheel based on clustering technology. To avoid misdiagnosis or loss of the state, a twice-cluster method is employed in the proposed method. Following conclusions are drawn in this study:

(1) It is not feasible to use 1D correlation dimension for state recognition of a bearing since the dimension fluctuates and its distribution is ruleless.

(2) 3D correlation dimension has potential to diagnose the state of a bearing, but it may lead to misdiagnosis or loss of the state during diagnosis process.

(3) 3D correlation dimension based on twice-cluster of K-medoids is applicable to diagnose the state of a bearing and its accuracy is very high if the state sphere representing corresponding bearing state has been well trained.

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