Acta Technica 62 No. 1B/2017, 69–78

Fault diagnosis methods of rotating machinery based on mathematical morphology

Jumei Zhang[1]

Abstract. To make a fault diagnosis of rotating machinery, it is necessary to use the Local Characteristic-scale Decomposition (LCD) to remove the noise before the fractal method. The major reason is that the fractal method is sensitive to mechanical noise. LCD and mathematical morphology method are combined for the diagnosis of mechanical failure, and in this ways, more accurate results can be obtained than that under the box dimensions. In addition, the morphological fractal dimension is used to calculate the fractal dimension of the main component, and the degree of discrimination of each state can be clearly depicted by curve description. And the results showed that the fault state of rolling bearing can be effectively identified and fault diagnosis can be realized. At last, it is concluded that the method based on LCD decomposition and morphology fractal dimension can successfully do the fault diagnosis, which has great application value and good prospect.

Key words. Mathematical morphology, rotating machinery, LCD, fault diagnosis.

1. Introduction

With the development of economic globalization and science and technology, people had a higher request in the stable and efficient operation of the machinery and equipment in industrial. More and more attention had been paid to the equipment fault diagnosis technology. Rolling bearings are one of the most commonly components used in mechanical equipment, but they are also particularly vulnerable to damage, which is detrimental to the life of the entire system and normal production. So, it is necessary to detect and diagnose the failure state of machinery and equipment bearing.

In 1991, Koskinen extended the traditional mathematical morphology operator, and proposed soft mathematical morphology. Soft mathematical morphology means to replace the maximum and minimum operation in the traditional mathematical morphology as weighted ordering statistics. Its structure elements include two parts:

[1]Weinan Normal University, Weinan, Shaanxi, 710000, China

hardcore and soft boundary [1]. In 1990s, Sinha and other scholars introduced fuzzy theory into traditional mathematical morphology, and put forward fuzzy mathematical morphology. It used membership function to achieve the operation between structure operator and fuzzy images. As a result, compared with traditional mathematical morphology, fuzzy mathematical morphology has stronger noise suppression capability. At present, application of morphology based on single scale structure element is widely studied. Zhang Lijun used generator signal for the filtering processing, and then he applied morphology non-sampling wavelet for the rotor wave processing and Shen Lu made use of morphology wavelet and morphology non-sampling to make filtering processing of gearing and rolling, respectively [2]. All of these studies laid a foundation for the further study of mathematical morphology. Mechanical fault diagnosis is an actually signal processing. The fault signal is typically non-linearity and non-stationarity. The fractal dimension of the mathematical morphology can effectively analyze and characterize the nonlinear behavior of the fault signal. However, the measured bearing vibration signal often contains a lot of system background noise. Because the mathematical morphology fractal dimension is very sensitive to noise, so the measured signal must be denoised to get the accurate fractal dimension, and the traditional linear filter is usually not competent [3]. A new adaptive time-frequency analysis method—Local Characteristic-Scale Decomposition (LCD) is proposed, which can decompose the vibration signal into a single rotation component with physical meaning at instantaneous frequency. In this paper, the LCD method is combined with the fractal dimension of the morphology, and the vibration signal is decomposed by the LCD. The components of the main characteristic frequency are used as the fault signals to be analyzed. The morphological fractal dimension is used to calculate the fractal dimension of the main component, and the degree of discrimination of each state can be clearly depicted by curve description, which can effectively identify the fault state of rolling bearing and realize the fault diagnosis of rolling bearing.

2. Materials and methods

2.1. Mathematical morphology

The basic idea of using mathematical morphology to measure the complexity of the nonlinearity of vibration signals at different scales is that the results of covering the one-dimensional vibration signals with planar set$B$ in the process of dealing with one-dimensional fault signals are regarded as one-dimensional structural elements g to detect the signal, which is an equivalent method, in which the structural element is the upper bound of the planar set B. Based on the above-mentioned idea, the concrete method steps are as follows [4]: the one-dimensional discrete vibration signal $f(n)\,(n = 0, 1, \cdots, N)\,, g(m)$ is the one-dimensional unit structure element defined on $G = \{0, 1, 2, \cdots, M-1\}$. One-dimensional morphology corrosion and expansion are carried out to measured signal, and the scale $\varepsilon = 0, 1, 2, \cdots, \varepsilon_{\max}$ represents the discrete scale range. The vibration signals are expanded and corroded by one-dimensional discrete function as the unit structure element at each scale.

2.2. Analysis of simulation signal

In order to verify the effectiveness of fractal dimension estimation method based on mathematical morphology, Weierstrass cosine function (WCF) is used as the fractal signal, which is defined as [5]:

$$W_{\mathrm{H}}(t) = \sum_{k=0}^{\infty} \gamma^{-kH} \cos\left(2\pi\gamma^{k} t\right), \quad (0 < H < 1) . \tag{1}$$

In the formula, $\gamma > 1$. WCF is a continuous but not differentiable signal, and the fractal dimension of W_{H} is $D = 2 - H$ in theory. The sampling frequency of the simulation signal is 1024 Hz, the number of sampling points is 2048, and the parameters are set to $\gamma = 5$ and $k = 20$ [6–7]. Table 1 shows the WCF signals of three different dimensions ($D = 1.4, 1.6, 1.8$).

At present, the Box-counting method is the most widely used signal estimation method, but because the box dimension divides the grid regularly, there is a problem that the fractal dimension estimation is inaccurate. However, the mathematical morphology is not affected by these factors, and the calculation results are more accurate [8]. Table 1 is the result of using box counting and fractal dimension estimation to deal with the signal. From Table 1, it can be seen that the fractal dimension of the box counting method is generally low, the error is larger than the mathematical morphology, and the morphology is more accurate, and the computational efficiency of mathematical morphology is higher than the box dimension.

Table 1. Fractal dimension estimation of WCF signal

Methods	Actual value	$D = 1.4$	$D = 1.6$	$D = 1.8$
Box-counting method	Estimated value	1.3497	1.4997	1.6553
	Relative error	3.59 %	6.26 %	8.04 %
Morphological method	Estimated value	1.4386	1.6200	1.8076
	Relative error	1.97 %	1.25 %	0.42 %

The WCF signal was morphologically covered with structural elements of sizes 32 and 64. Figure 1 shows the expansive corrosion results of $W_{0.4}(t)$ at scales 32 and 64.

2.3. LCD decomposition method

LCD's premise is that all the signals are regarded as to be composed of different single-component ISC, and any two ISC components are independent of each other. So that the signal $x(t)$ can be decomposed into the sum of the independent components, and these feature-scale components meet the following two conditions:

In the whole interval, the maximum value is positive, the minimum is negative, and there is monotony between any two adjacent. In the whole interval, the extreme point of the component is set to $(\tau_{\mathrm{k}}, X_k), k = 1, 2, \cdots, M$, M being the number of extreme points [9]. Therefore, the straight line

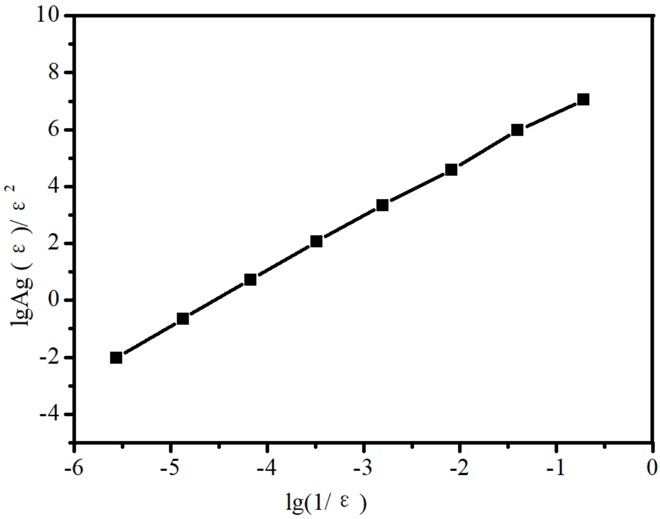

Fig. 1. Double logarithmic curve of $W_{0.2}(t)$

$$l_k \left\{ y = X_k + \frac{X_{k+2} - X_k}{\tau_{k+2} - \tau_k} (t - \tau_k) \right\}$$

is determined by any two adjacent extremums (maximum or minimum) (τ_k, X_k) and (τ_{k+2}, X_{k+2}) in the data segment, the ratio of the value A_{k+1} of this line in τ_{k+1} and the function value at this point are unchanged, as shown in Fig. 2.

$$\frac{A_2}{X_2} = \cdots = \frac{A_6}{X_6} = \cdots \mu \,. \tag{2}$$

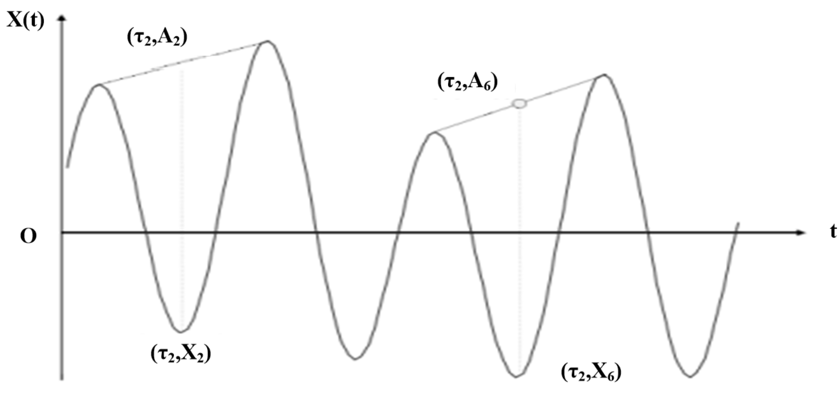

Fig. 2. Conditions for the intrinsic scale component

In the simulation signal, μ may not change, but in the actual signal, its value must not be so stable, so it can be changed in a certain range of permission.

The general form is [10]:

$$aA_{k+1} + (1-a)\,X_{k+1} = 0, \quad a \in (0,1)\ , \tag{3}$$

$$A_{k+1} = X_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k}\right)(X_{k+2} - X_k)\ . \tag{4}$$

When $a = 0.5$, $A_{k+1} = -X_{k+1}$.

3. Results

The following signals are used to investigate the decomposing effect of the LCD:

$$x\,(t) = x_1\,(t) + x_2\,(t) = [1 + 0.5\cos(20\pi t)]\sin\left(200\pi t + 200t^2\right) + \sin(40\pi t)\ . \tag{5}$$

The simulation signal is composed of an amplitude modulation and frequency modulation signal and a sinusoidal signal.

From the decomposition results of the LCD, it can be seen that this method can decompose the frequency components in the simulation signal very well. CISC3 has a small fluctuation after processing the end effect by the extension method, and the processing result is ideal. The results show that LCD is an effective and feasible decomposition method.

In the case of adaptive time-frequency analysis, such as Empirical Mode Decomposition (EMD) and Local Mean Decomposition (LMD), these methods only give their components with the physical meaning [11]. The conditions that the intrinsic mode function (IMF) component EMD definite by EMD or the PF component in LMD need to meet are the sufficient conditions of instantaneous frequency with the physical meaning, but not a necessary condition, that is, as long as certain conditions are met, a single component signal can have physical significance. In addition, the cubic spline function is used to deal with the end-effect in the EMD method, which often has over-envelope, under-envelope phenomenon in the formation of the upper and lower envelopes, and the mode aliasing is serious. However, the LMD method has more end-effects than the EMD method, and the range of the LMD method is small, but the LMD algorithm has its own limitations [12]. In the decomposition of LMD algorithm, it uses the moving average algorithm to calculate the local mean function and local envelope function, while the moving average algorithm is a cycle of multiple iterations, so the calculation is very large. For these reasons, the components defined by EMD and LMD often result in unreliable methods. Therefore, this paper combines a new instantaneous frequency with physical meaning of the decomposition method LCD with the morphology. Experiments show that this method is effective.

The experimental data is from the bearing data of deep groove ball bearing fault whose bearing model is 6205-2RS JEM SKF in United States West Reserve University [13]. The four failure types of the rolling bearing failure in normal test platform, rolling element failure, inner ring failure and outer ring failure are used.

It can be seen from Fig. 3 that when the vibration signal is not denoised, the fractal dimension of the rolling element fault has two sudden ups and down at the position of sample 4 to 8, which cause the interference by overlapping with the curve of the normal state and the inner fault state. The curve of fractal dimension overlap twice in inner-circle fault and in the normal state, which makes the fault state unrecognizable. As the LCD method can decompose the original signal from high frequency to low frequency into several components, the high frequency component is often the best to reflect the fault feature information [14]. Therefore, usually the first component after the characteristic scale decomposition is calculated, and the vibration state of each failure can be effectively discriminate. Figure 3 is the first intrinsic component of the signal corresponding to Fig. 4.

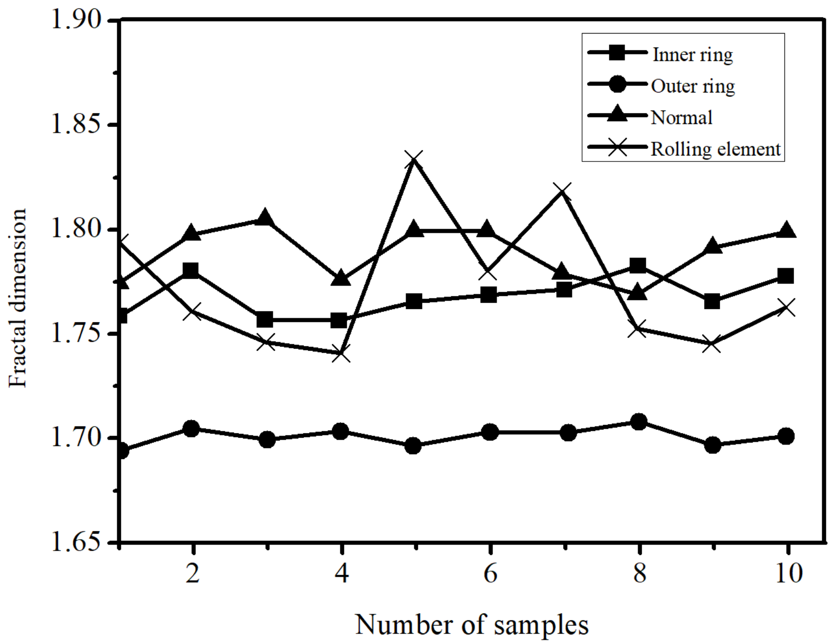

Fig. 3. Morphology fractal dimension of bearing faults signal

From the decomposition results of the LCD, it can be seen that this method can decompose the frequency components in the simulation signal very well, and the CISC3's fluctuation is small, and the processing result is ideal after dealing with the endpoint effect by the extension method. The results show that LCD is an effective and feasible decomposition method [15]. The first component is analyzed and processed by mathematical morphology, and a signal fractal is obtained as shown in Fig. 5. From the figure we can see that the fractal dimension is maximum in normal state of the bearing. Because there is no significant impact from the outside world

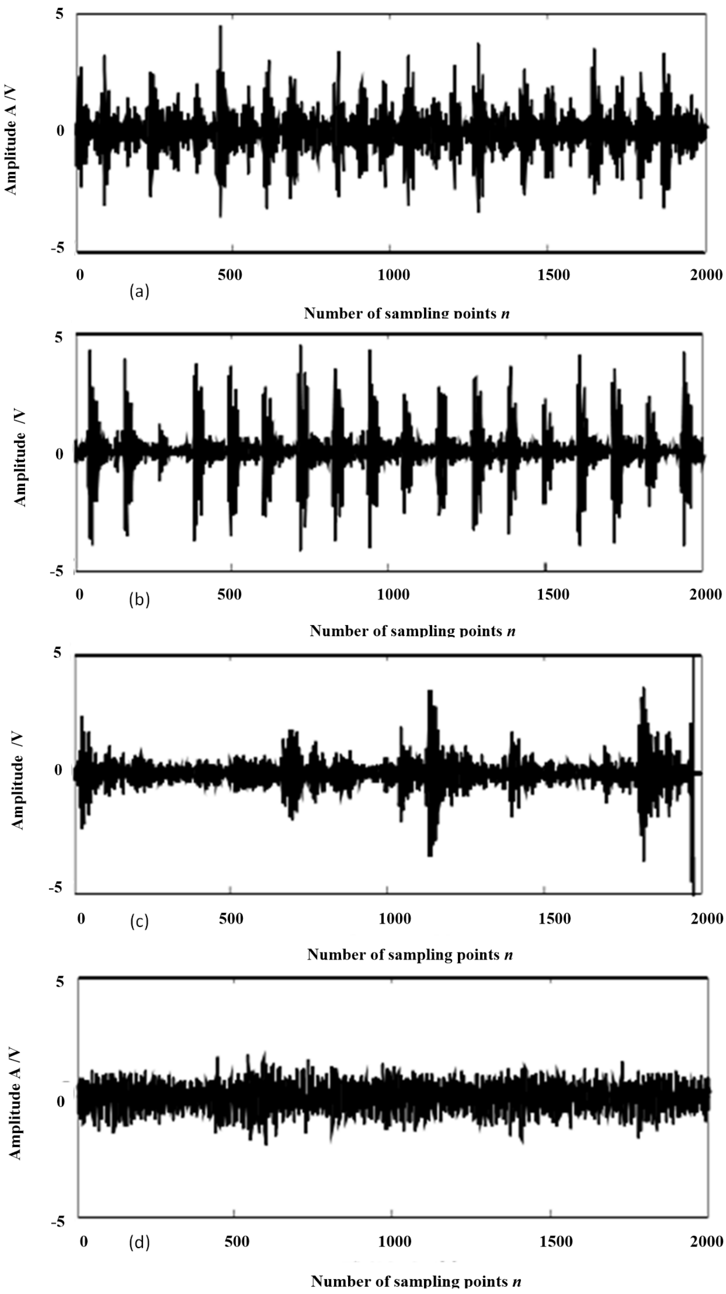

Fig. 4. The first component of the signal of four bearing fault conditions: (a)–first component of the rolling bearing inner ring, (b)–first component of the rolling bearing outer ring, (c)–first component of the rolling element of rolling bearing, (d)–first component of the normal state of rolling bearing

in normal state, and it is similar to the random signals in probability distribution, the randomness is equivalent to the instability in various states, which also coincides with the definition of the dimension in the mathematical morphology. While the inner ring fault and the rolling element failure are fault signals with obvious impact, so their dimensions are relatively small, but there is not much difference between the dimensions. While the impacts to the outer ring are relatively large, and the features are relatively obvious, so the dimension is smaller than the other fault types [16]. Although the fractal curves of the inner ring and the rolling element has once intersected, this does not affect the accurate discrimination of them. The fractal dimension of mathematical morphology based on LCD can distinguish the four states better. The experimental results show the effectiveness and feasibility of the method.

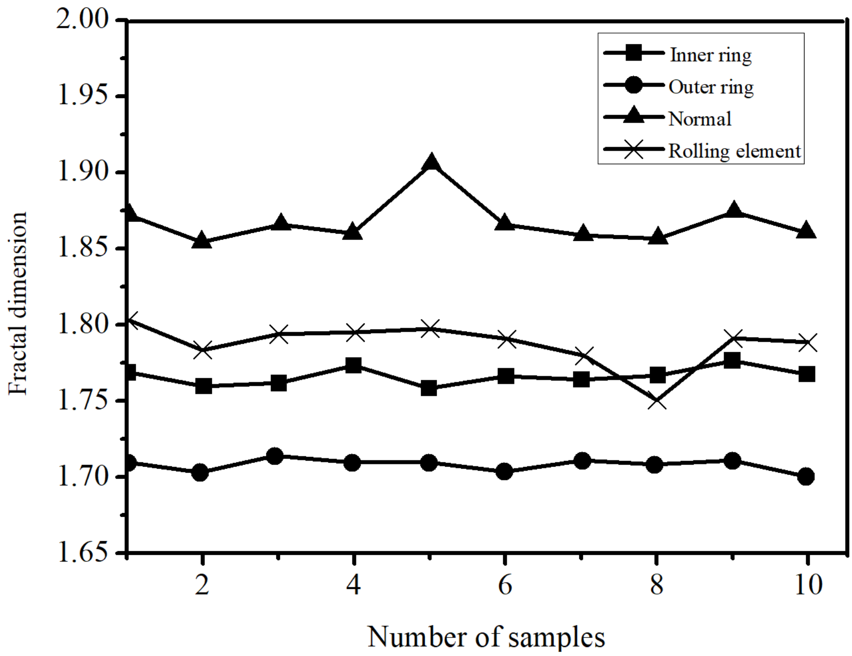

Fig. 5. The first CISC morphology fractal dimension of bearing fault signals

4. Conclusion

In this paper, a fault diagnosis method of rolling bearing based local feature scale decomposition and fractal dimension is studied. The simulation results showed that the mathematical morphology has better accuracy and computational efficiency than the box dimension. The LCD method can separate the fault signal characteristic component from the background noise or other interference signal to improve the accuracy of the fault identification. After the fault signal is decomposed by the LCD method, the ISC component of the characteristic fault signal is obtained. The fractal dimension of each ISC component is calculated and used as the characteristic parameter to judge the state. At last, the normal bearing, rolling element failure, inner ring fault and outer ring fault are analyzed. The results show that the method based on LCD decomposition and morphology fractal dimension can effectively realize the diagnosis of rolling bearing fault state.

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Received June 29, 2017