911. A quantitative diagnosis method for rolling element bearing using signal complexity and morphology filtering

Kuosheng Jiang[1], Guanghua Xu[2], Lin Liang[3], Guoqiang Zhao[4], Tangfei Tao[5]
[1, 2, 3, 4, 5]School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, China
[2]State Key Laboratory for Manufacturing System Engineering, School of Mechanical Engineering Xi'an Jiaotong University, Xi'an 710049, China
[5]Key Laboratory of Education Ministry for Modern Design and Rotor-Bearing System Xi'an 710049, China
E-mail: [1]*jiangkuosheng333@stu.xjtu.edu.cn*, [2]*xugh@mail.xjtu.edu.cn*, [3]*lianglin@mail.xjtu.edu.cn*, [4]*zimeyzhao@126.com*, [5]*taotangfei@mail.xjtu.edu.cn*

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Abstract. This paper considers a quantitative method for assessment of fault severity of rolling element bearing by means of signal complexity and morphology filtering. The relationship between the complexity and bearing fault severity is explained. The improved morphology filtering is adopted to avoid the ambiguity between severity fault and the pure random noise since both of them will acquire higher complexity value. According to the attenuation signal characteristics of a faulty bearing the artificial immune optimization algorithm with the target of pulse index is used to obtain optimal filtering signal. Furthermore, complexity algorithm is revised to avoid the loss of weak impact signal. After largely removing noise and other unrelated signal components, the complexity value will be mostly affected by the bearing system and therefore may be adopted as a reliable quantitative bearing fault diagnosis method. Application of the proposed approach to the bearing fault signals has demonstrated that the improved morphology filtering and the complexity of signal can be used to adequately evaluate bearing fault severity.

Keywords: morphology filtering, signal complexity, rolling element bearing, fault severity, quantitative diagnosis.

1. Introduction

Rolling element bearing is the most common machine element and it is of essential importance to almost all forms of rotating machinery. In order to prevent failures various condition monitoring techniques have been developed. Most of them are qualitative diagnosis methods considering: (i) Does damage exist? (Detection), (ii) Where is the damage? (Localization), and (iii) What is the sort of damage? (Classification). However this is not sufficient and a proper maintenance decision can be made only when fault severity is accurately assessed, i.e. (iv) How much and how serious is the damage? (Quantification) [1].

The most commonly used quantitative diagnosis methods for fault severity are energy-based. In the work by Loutridis [2], energy index was successfully applied to the gearbox fault feature via the empirical mode decomposition method. Covacece and Introini illustrated that auto- and cross-power spectrum of ball bearing of helicopter gearbox increased their magnitudes as the fault developed [3]. According to the work by Dalpiaz et al. [4], the cepstrum showed an increasing trend as the gear crack propagated. Shao and Nezu [5] investigated the relationships among fault size (or severity), the kurtosis and the learning ratio of adaptive noise cancellation for faulty bearing signals. Williams et al. [6] used multiple sensors to monitor bearing condition in the run-to-failure test. They represented fault growth in terms of time-domain indices such as RMS value, kurtosis and crest factor calculated from the data. The AB proposed the Shock Pulse Method proposed by SPM Instrument used vibration sensor to collect the impact signal generated when the rolling element goes across a defect position. The growth rate of impact value is used to evaluate the severity degree of bearing faults. With the second order cyclo-stationary theory and loop coherent analysis, Dong Guangming [7] proposed to use the cycle frequency energy index to quantitatively characterize the damage severity degree of rolling bearings.

However, the vibration amplitudes and/or their feature indexes (Mean, RMS, variance, etc.) obtained from the time domain or the amplitudes of the components usually change slightly as the fault severity increases, while the shape of signal waveform change significantly. For instance, Qu and Shen [8] demonstrated that rotor crack fault cause the second harmonic and harmonic components of vibration signal increase obviously, but the amplitude of the signal can not reflect the fault. Therefore, we need to find a better indicator that not only reflects the changes of the signal shape or the spectrum structure, but also has same effect of above index. In fact, when the shape of signal waveform and the spectrum structure change, then the complexity of the signal changes as well. Chen [9] proposed the method of four-dimensional information entropy distance, which is a new quantitative diagnostic index for rotor vibration faults based on the quantitative diagnostic study for rotating machinery vibration failure integrated information entropy. It took into account the characteristics of all symptom domains of the vibration signal, thus it had better results to distinguish failure. It is pointed out that current widespread lack of integration of quantitative diagnostic method is to focus only on the fusion characteristics in each domain of the signal in a single state, while neglecting the process variation of the fault signal. By defining the information, the physical quantity that could describe the variation of this process, the diagnostic methods based on process information integration could be studied, which would become the development direction of the integration of quantitative fault diagnosis technology. Yan and Liu [10] used permutation entropy to investigate the work status characterization of rotary machines and verified that the effectiveness of the permutation entropy on characterizing working status of rolling element bearings. However the complexity of dynamic system includes entropy, fractal dimension, Lyapunov indicator, correlation dimension etc. It is obvious that the calculation of Lyapunov exponent and correlation dimension requires large amounts of data, and the entropy method is too complex for real-time monitoring. So Dou and Zhao [11] proposed a normalized Lempel-Ziv complexity indicator for the assessment of the deterioration of the bearing state. It considered the relationship between fault degree and signal nonlinearity, confirmed that in the measure of the outer ring damage this indicator was incremental with the exacerbated failure, thus provided a new way of quantitative diagnosis of bearings. However, there are still some problems to be solved, as the complex indicator of serious fault and random noise are both close to 1, then if we get a high index value, it is difficult to discern whether it is due to a heavy fault or noise.

This paper mainly investigates two novel ideas. The first is to use the revised complexity of signal to realize the quantification diagnosis for rolling element bearing. The second idea is to use the improved morphology filtering based on immune optimization to fully restrain the background noise and extract the entire impulsive attenuation signal.

The proposed method is appropriate for assessing the operating condition and faulty severity of rolling bearings during all of the life-cycle. The remainder chapters of this paper are organized as follows. In section 2, the basic theoretical background is introduced, the morphological filter and the optimization method of structural elements parameter is introduced. The algorithm of time complexity and the revised Lempel-Ziv algorithm are introduced. Section 3 gives a simulation study and analysis to verify the proposed method. In section 4, a rolling fatigue test and fault experiments are introduced and the results show that the proposed method could be effectively utilized to quantitatively evaluate the severity of rolling bearing fault.

2. Theoretical background

In this section, the revised Lempel-Ziv complexity algorithm is used to quantitatively evaluate the severity of rolling element bearing fault. Improved morphology filtering is adopted to avoid the ambiguity between severity fault and noise since both of them will get higher complexity value.

2.1 The introduction of complexity measure algorithm

The complexity of signal increases when multi-frequency components exist. For bearings, contact pressure between two mating parts changes when a fault occurs and its variation leads to amplitude and frequency modulations. Therefore, with the development of the fault, the complexity degree of signal changes as the fault augments variation of the contact pressure between two mating parts.

As to the outer-race fault, the complexity degree value increases as fault size increases because of the frequency modulation. However, the complexity degree value of inner-race fault decreases because of the modulation effect of the non-uniform load distribution. The amplitude modulation makes the signal globally display low-frequency oscillation, it makes the signal randomness drop and the order strengthens, which tends to be lower Lempel-Ziv value. In addition, the complexity degree value of boll fault is the biggest, as the ball is always slipping while rolling, makes the contact of the inner and outer unstable, which leads to higher complexity value.

The definition of complexity was initially proposed by Kolmogorov in 1965, characterized the bits of a computer program that is needed by a sequence consisting of "0" and "1" [12]. In 1976, Lempel and Ziv proposed a specific algorithm for the calculation of such complexity and its size reflects the information content of time series, and the calculation process is as follows [13]:

Consider a string $S = \{s_1, s_2, \cdots, s_N\}$, firstly we need to turn it into a binary sequence consisting of "0" and "1", the usual practice is to obtain the average m of the initial sequence, and the original sequence should be reconstructed by the following rules:

$$S_i = \begin{cases} 1, x_i > m \\ 0, x_i < m \end{cases} \tag{1}$$

For the string of characters $S = \{s_1, s_2, \cdots, s_r\}$ that has been formed in this [0,1] sequence, we can insert a character s_{r+1} or a string of characters $Q = \{s_{r+1}, s_{r+2}, \cdots, s_{r+m}\}$, both of them composed a string *SQ* Let *SQV* is the string which is the original *SQ* string minus the last character from it. If *Q* belongs to the "words" that is already in *SQV*, then put this character in the back, and call it the "copy". If not, then call it the "Insert", and separate the front and rear with a ".". Then consider all the characters in front of "." as *S*, and repeat the above steps.

According to Lempel and Ziv's research, for almost all binary sequences, their complexity will always approach to the value of $b(n)$:

$$b(n) = \lim_{n \to \infty} c(n) = n / \log_2 n \tag{2}$$

So $b(n)$ is the asymptotic behavior of the random sequence, and is used to normalize $c(n)$, which is known as the relative complexity:

$$C(n) = c(n) / b(n) \tag{3}$$

Usually $C(n)$ is used to characterize the changes of the time series complexity, which reflects the closeness of a time series. When the time series is a completely random sequence $C(n)=1$ and when the time series is a periodic sequence $C(n)=0$.

2.2 Improved binarization rules for complexity measure algorithm

a. The problem of complexity measurement

Kolmogorov measure is defined on the basis of the binary sequence consisting of 0 and 1. For the collected digital signals, they need to be translated into binary sequences. The Kolmogorov measure strategy is correctly reflecting the system of nonlinear changes only under reasonable binarization rules and the traditional binary rule is taken for the data points whose values are higher than the average as one, and the others are taken as 0. It is obviously unreasonable to deal with the bearing vibration signal directly in this way: it converts the characteristic component whose signal amplitude is less than the average to 0, resulting in the loss of information in the original vibration signal, as shown trapping part in Fig. 1.

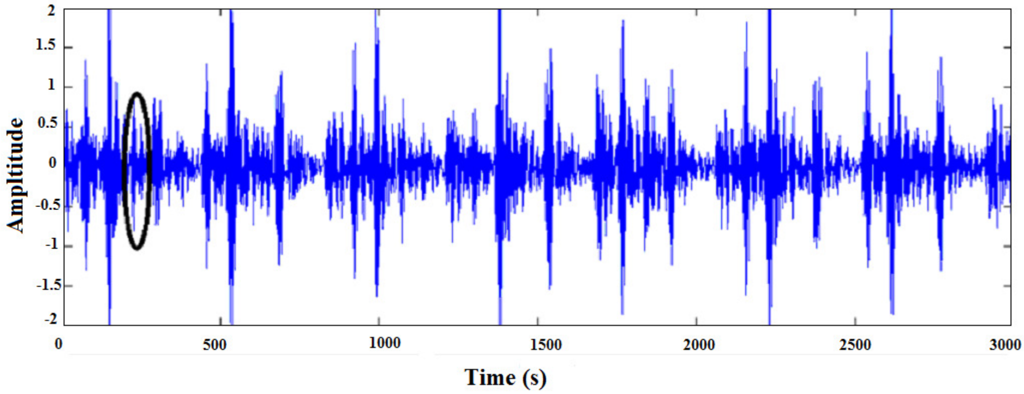

Fig. 1. The waveform of rolling element bearing

b. The improved algorithm

The traditional complexity measure algorithm rules are as follows:

Assume that $x(n)=\{x_1,x_2,\cdots,x_N\}$ is the original bearing vibration signal, and its average is:

$$x_p=\left[\sum_{i=1}^{N}x_i\right]/N \tag{4}$$

Calculate the absolute deviation of $x(n)$, x_p and:

$$y(n)=\{y_1,y_2,\cdots,y_N\} \tag{5}$$

where $y_i=\left|x_i-x_p\right|$, and calculate the average of the new sequence $y(n)$:

$$y_p=\left[\sum_{i=1}^{N}y_i\right]/N \tag{6}$$

Then the binary sequence is $S=\{s_1,s_2,\cdots,s_N\}$, where:

$$S_i=\begin{cases}1, y_i>y_p\\ 0, \text{others}\end{cases} \tag{7}$$

Under this rule, high amplitude vibration shock wave is converted into 1, and other parts of the conversion are 0. This binarization rule retains some useful information in the bearing vibration signal, but some low amplitude impact component has been ignored, and all will be converted to 0. Therefore we propose the following transformation rules: calculate the absolute difference sequence of $x(n)$:

$$D(n) = \{D_1, D_2, \cdots, D_N\} \tag{8}$$

where:

$$D_i = \begin{cases} 0, & i = 1 \\ |x_i - x_{i-1}|, & \text{others} \end{cases} \tag{9}$$

Calculating the average of the difference sequence:

$$A = \left[\sum_{i=1}^{N} D_i\right] / N \tag{10}$$

The original bearing vibration signal $x(n)$ is converted into symbolic sequences consisting of "0" and "1", $b(n) = \{b_1, b_2, \cdots, b_n\}$, where:

$$b_i = \begin{cases} 1, & y_i > y_p \text{ or } D_i > A \\ 0, & \text{others} \end{cases} \tag{11}$$

In accordance with this conversion rule, the shape of the impact components waveform in the original vibration signal will be converted to 1, and the rest components are converted to 0. The obtained binary sequence could reserve more complete useful information in the original bearing vibration signal. The implementation of proposed algorithm is shown in Fig. 2.

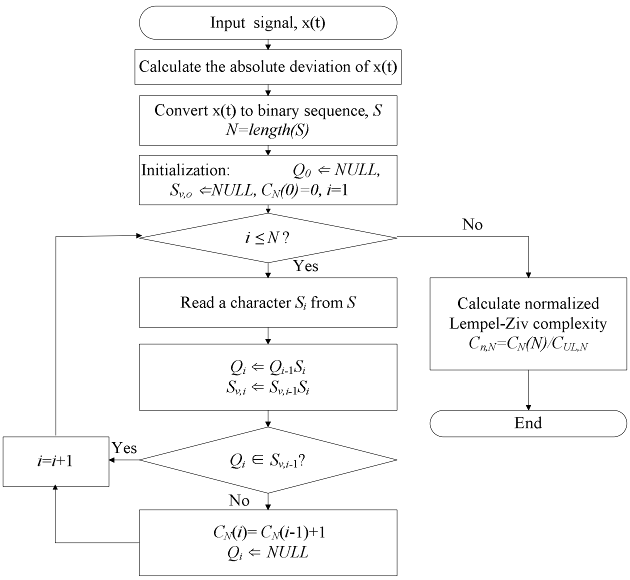

Fig. 2. The proposed algorithm flow diagram

2.3 The improved morphological filtering algorithm

Yan and Gao [14] used the complexity to obtain different complexity values for different fault sizes of cylindrical roller bearing. According to results, the normalized Lempel–Ziv complexity approaches the upper limit, around 1.0, as a fault develops. However, the measured signal is contaminated by noise. This may increase the complexity value and may result in false diagnosis. In fact, the pure random noise has a normalized complexity value around 1.0. As illustrated later, the Lempel–Ziv complexity of the signal of severe bearing faults is close to 1.0.

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Therefore, it is difficult to distinguish the sources (noise or fault) of the complexity value, and a time-domain nonlinear filtering method is need.

Morphological filtering is a time-domain nonlinear method. It can eliminate noise effectively while preserving the original signal in some of the essential features of information. Koskinen found flexible morphological filters on the basis of morphological filtering, not only retaining many fine features of the standard morphological filters, but also having better robustness. From the morphological point of view, bearing fault characteristic waveform is typical of the impact attenuation signal. As the design of structure element of morphological filtering is quite flexible, it can fully restrain the background noise and extract the entire impulsive attenuation signal including weak impact signal. And also, since the morphological filtering is a time-domain filtering, it is more suitable for pre-processing signals before the calculation of complexity.

a. Theory of morphological filter

Morphological filter with functional structure element for one-dimensional time series data was first presented by Magaros and Schafer in 1987 [15], which consists of four basic operations:

Erosion:

$$(f\Theta g^{s})=\min_{\tau\in D}\{f(\tau)-g(-(t-\tau))\} \tag{12}$$

Dilation:

$$(f\oplus g^{s})=\max_{\tau\in D}\{f(\tau)+g(-(t-\tau))\} \tag{13}$$

Opening:

$$(f\circ g)(t)=[(f\Theta g^{s})\oplus g](t) \tag{14}$$

Closing:

$$(f\bullet g)(t)=[(f\oplus g^{s})\Theta g](t) \tag{15}$$

where $f(t)$ is the original signal and $g(t)$ is the structure element. $g^{s}(t)$ is the reflection of $g(t)$ defined as $g^{s}(t)=g(-t)$. D means the set of real numbers. The notation $\oplus$, Θ, $\circ$ and $\bullet$ indicate Minkowski addition, Minkowski subtraction, opening and closing operations, respectively. The basic properties of the operations can be described as follows: Erosion of $f(t)$ by structure $g(t)$ reduces the peaks and enlarges the minima of $f(t)$, while dilation of $f(t)$ by $g(t)$ increases the valleys and enlarges the maxima of $f(t)$. Opening of $f(t)$ smoothes the signal $f(t)$ from below by cutting down its peaks, and closing smoothes the signal from above by filling up its valleys. Thus, closing and opening operation can be applied to detect positive and negative impulses, respectively.

Nikolaou and Antoiadis employed closing operation to extract impulsive components from the original signals. According to the property of morphological operation, only positive impulses are detected. However, there are sharp peaks with both positive and negative amplitude in vibration response of machines with defects, such as outer race fault in rolling bearings. Closing operation indeed extracts some useful information from the signal, but looses geometric characteristics of the signal which may help in fault diagnosis. In order to detect bi-directional impulsive components, the morphological algorithm can be first applied with opening (or closing) operator followed by closing (or opening) operator, which are defined as follows:

Open-closing operation:

$$OC(f(t))=f(t)\circ g_{1}(t)\bullet g_{2}(t) \tag{16}$$

Close-opening operation:

$$CO(f(t)) = f(t) \bullet g_1(t) \circ g_2(t) \quad (17)$$

where $g_1(t)$ and $g_2(t)$ are different structure elements. However, both open-closing and closing-opening operation can lead to a statistical deflection of amplitude, i.e., the result of open-closing operation has lower amplitude than original signal and the result of close-opening operation has larger amplitude than original signal. This maybe will affect the result of fault diagnosis. In this paper, we utilize an average weighted combination of open-closing and close-opening operation as follows:

$$M_{aw}(f(t)) = \frac{[CO(f(t)) + OC(f(t))]}{2} \quad (18)$$

With Eq. (18), not only the bi-directional impulses can be extracted but also the statistical deflection of amplitude caused by individual open-closing or close-opening operation is avoided.

b. Selection of structure element

Structure element is sticking point of morphological filtering and subtle change in structure element may bring quite different detection effect. The basic principle to design structural elements is to select the structural element which is similar to the geometric characteristics of the target signal. The choice of structural elements includes the shape and size.

In this paper, two kinds of representative transient models are introduced as the structure elements for rolling bearing fault. Those are Morlet wavelet and Laplace wavelet, as given in the left side of Fig. 3. The periodic multi-transient models based on the two wavelets are shown in the right side of the Fig. 3, respectively. These two structure elements consist of single-side and double-side waveforms. They well match the non-stationary signal that contains transients due to impulsive-attenuation-type responses or time-varying dynamics.

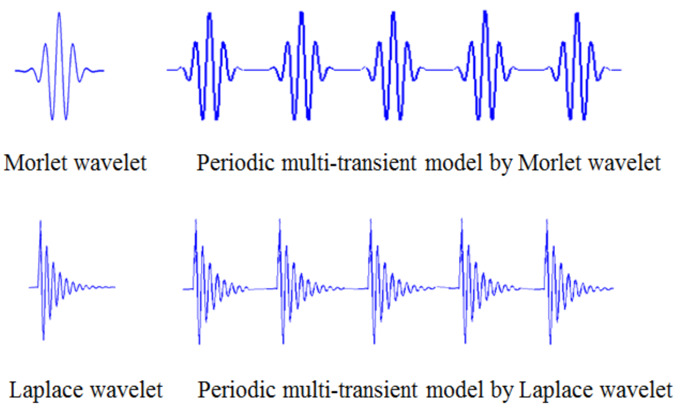


Fig. 3. The proposed structure element

Morlet wavelet is a double-side wavelet, and the parametric formulation of Morlet wavelet is as Eq. (19). Laplace wavelet is formulated as a complex, analytic, single-side damped exponential. The formulation of real part of Laplace wavelet is given as Eq. (20).

$$\psi_{Morlet}(f,\zeta,\tau,t) = \psi_{Morlet,\gamma}(t) = \begin{cases} e^{-\xi/\sqrt{1-\zeta^2}[2\pi f(t-\tau)]^2}\cos(2\pi f(t-\tau)), \tau - W_s \le t \le \tau + W_s \\ 0 \qquad \text{else} \end{cases} \quad (19)$$

$$\psi_{Laplace}(f,\zeta,\tau,t) = \psi_{Laplace,\gamma}(t) = \begin{cases} e^{-\xi/\sqrt{1-\zeta^2}\,2\pi f(t-\tau)}\cos(2\pi f(t-\tau)), \tau \le t \le \tau + W_s \\ 0 \qquad \text{else} \end{cases} \quad (20)$$

where the parameter set $\gamma = \{\omega, \zeta, \tau\}$ determines the wavelet properties. Parameters ω, ζ, τ denote frequency $\omega \in R^+$, damping ratio $\zeta \in [0,1) \subset R^+$, and time index $\tau \in R$, respectively. By carefully choosing parameters, a structure element that closely matches the shape of mechanical impulse can be constructed. It is obvious that parameter selection is a multimodal optimal problem.

c. Parameter optimization for structure elements with immune artificial system

The artificial immune algorithm simulates the natural immune system. It retains outstanding individuals in the process of optimization and makes it always get better. Therefore immune-based optimization algorithm is adopted to optimize the parameters of structural elements of bearing failure. It can not only shorten the optimization time, but also achieve higher optimization precision, so as to achieve a better fault waveform detection for rolling bearing. The basic process of immune-based optimization of morphological filtering is: given the fault vibration signal, and designed proper morphological filtering algorithm and construct structural elements. The affinity index can measure quantitatively the performance of structure element individual in the antibody population. With the clone selection, antibody mutation, and immune selection, the structural elements of the vibration signal morphological filtering can be achieved the best detection results. Then the immune clonal selection algorithm used for parameter optimization is shown in Fig. 4.

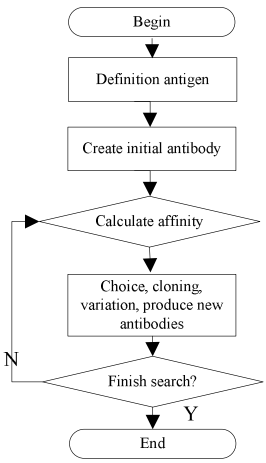


Fig. 4. Immune clonal selection algorithm

Let $s(t)$ denote the input rolling element bearing fault signal, the affinity I_f index is defined as follows:

Firstly, we calculate the impulse indicator I_f of signal $x(t)$:

$$I_f = \hat{x} / \bar{x} \tag{21}$$

where:

$$\hat{x} = \max\{|x(t)|\} \tag{22}$$

$$\bar{x} = \frac{1}{N}\sum_{t=1}^{N} x(t) \tag{23}$$

It is obvious that the impulse index I_f reflects impact degree of the prominent composition in the feature extraction results. Therefore I_f reflects prominent degree of impact component after filtering the background noise.

3. Quantitative assessing via morphology filtering and the complexity degree

Combining with the morphology filtering and complexity, application of quantitative evaluation algorithm for rolling bearing fault is proposed. The flowchart is detailed in Fig. 5:

Step 1: Morphology filtering is applied to the measured signal.

Step 2: Calculate the impulse indicator I_f and with the immune optimization algorithm, the best filtering signal by optimal structure element parameters.

Step 3: Calculate normalized complexity of the measured after morphology filtering.

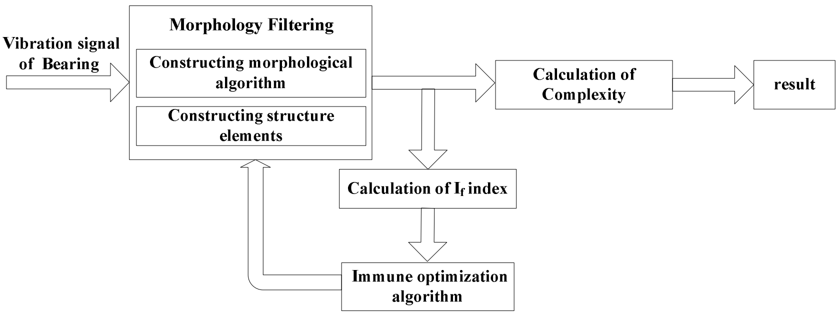


Fig. 5. Flowchart of fault severity quantitative assessment

4. Simulation verification

Two data sets are simulated in order to verify the performance of our method in quantitative assessing of fault severity of rolling element bearings. In order to test the verification of morphological filtering, the first data set is constructed with impulsive attenuation and noise as shown in Fig. 6(a). With the optimal structure element, impulse attenuation components of the original simulation signal are extracted in Fig. 6(b). The signal clearly reveals the characteristic impulse with the period as expected. The speed of impulse decay, the number of rebounds, and the amplitude of impulse all depend on the system damping coefficient, resonance frequency and signal transmission path. The second data sets are constructed with different typical signals, such as sinusoidal, sinusoidal with amplitude modulation, sinusoidal with frequency modulation, and white noise, and they are used to test the verification of complexity. Fig. 7 shows the increasing complexity of signal when frequency components changed, which means the complexity provides a quantitative tool for assessing the fault severity of rolling element bearing.

5. Application on defective rolling element bearings

5.1 Experimental setup

In order to validate the proposed methodology and truly reflect the real defect propagation processes, bearing run-to-failure tests were performed under normal load conditions on a specially designed test rig. The bearing test rig hosts four test bearings on one shaft. The shaft is driven by an AC motor and coupled by rub belts. The rotation speed was kept constant at 2000 rpm. A radial load of 6000 lbs is added to the shaft and bearing by a spring mechanism. All the bearings are force lubricated. An oil circulation system regulates the flow and the temperature of the lubricant. Fig. 8 shows the test rig and illustrates sensor placement. All failures occurred after exceeding the designed lifetime of the bearings that is more than 100 million revolutions.

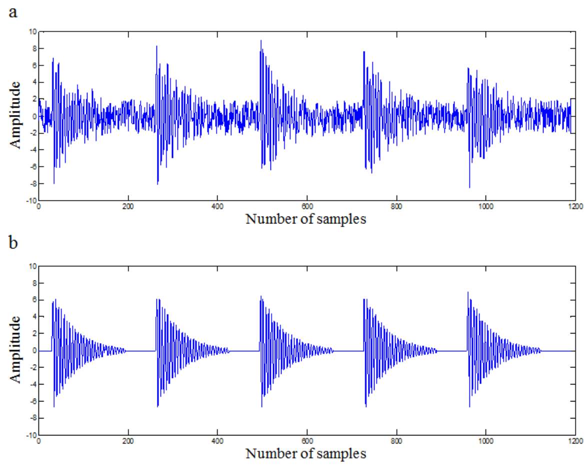


Fig. 6. Simulation of impulsive attenuation signal and morphological filtering

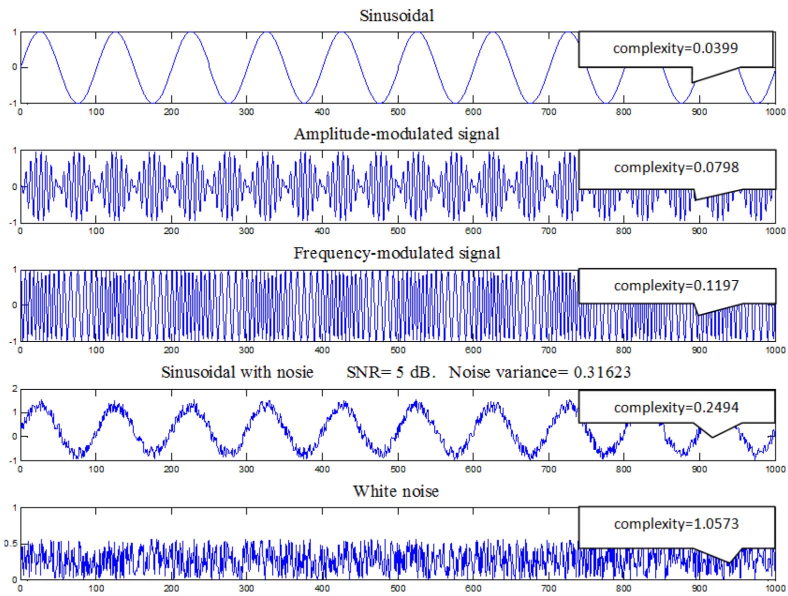


Fig. 7. Lempel-Ziv index values of different simulation of signals

A magnetic plug installed in the oil feedback pipe collects debris from the oil as evidence of bearing degradation. The test will stop when the accumulated debris adhered to the magnetic plug exceeds a certain level and causes an electrical switch to close. Four Rexnord ZA-2115 double row bearings were installed on one shaft as shown in Fig. 8. The bearings have 16 rollers in each row, a pitch diameter of 2.815 in, roller diameter of 0.331 in, and a tapered contact angle of 15.171. A PCB 353B33 High Sensitivity Quartz ICPs Accelerometer was installed on the housing of each bearing. Four thermocouples were attached to the outer race of each bearing to record bearing temperature for purposes of monitoring the lubrication. Vibration data was collected every 10 minutes by a NI DAQ Card-6062E. Data sampling rate is 20 kHz and data length is 20480 points. Data collection is conducted by LabVIEW program. The parameters of experiment bearing are as Table 1. BPFI, BPFO, BSF and FTF represent the characteristic frequency of inner race fault, outer race fault, ball fault and the cage fault.

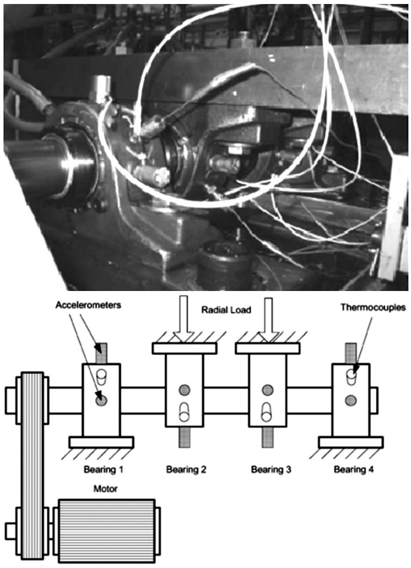


Fig. 8. Bearing test rig with illustration of sensor placement

Table 1. Parameters of the experiment bearing

Bearing designation	Ball numbers	Groove section size (inch)	Contact angle	BPFI (Hz)	BPFO (Hz)	BSF (Hz)	FTF (Hz)
ZA-2155 of Rexnord	16	0.331	2.815	296.9	263.4	139.9	29.55

5.2 Analysis of experimental results

Fig. 9(a) presents the vibration waveform collected from the outer race fault. The signal exhibits impulse periodicity because of the impacts generated by a mature outer race defect. However, due to noise, the periodic impulse feature is partly masked. Therefore, with the improved morphological filter, the entire impulsive signal given in Fig. 9(b) is extracted from background noise, rather than envelope of the signal.

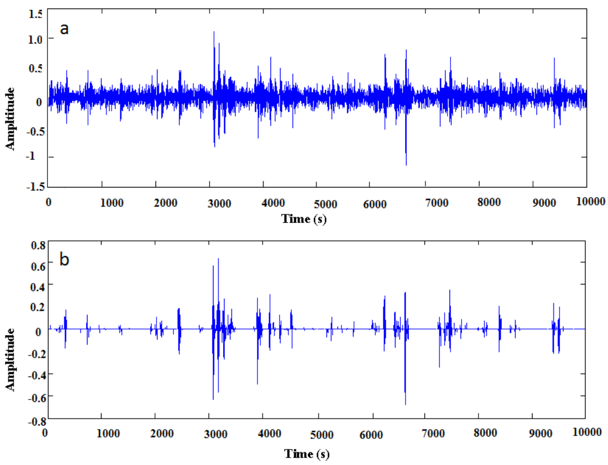


Fig. 9. The vibration waveform of bearing:
(a) outer race fault; (b) extracted by the improved morphological filter

Fig. 10 depicts the time domain features, mean, kurtosis, max and norm for the entire life cycle. It reveals that the overall trend of signal is rising, while during 7000 to 8000 minutes riding waves appear, which will lead to fault judgment. The reason for occurrence of riding waves is that the vibration energy strengthens with the constant expansion of crack in process of bearing degradation, and then abates with the diminishing contact surface roughness after a long time of friction. With the lengthening of the running time, the crack expands again. Those cycles lead to the forming of the waves. The fluctuating trend of time domain features cannot reflect the quantification of bearing degradation.

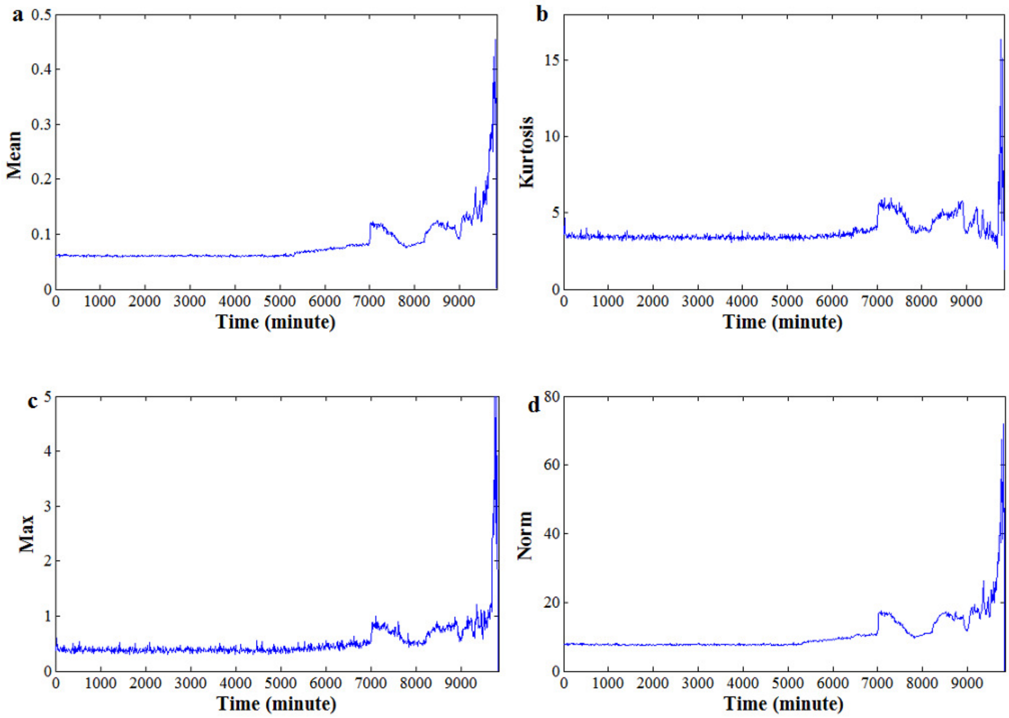


Fig. 10. The time domain feature (a) mean, (b) kurtosis, (c) max, (d) norm for the whole life cycle

The calculated Lempel–Ziv complexity values are presented in Fig. 11 and the shape of structure elements are also shown in Table 2. When compared with time feature provided in Fig. 11, the complexity of vibration signal increases as fault size increases because of the modulation of frequency. However due to the monotonous change of complexity, it is suitable for assessing fault severity. In phase I, the main waveform of the signal is white noise. After the process of morphological filtering, the complexity of the signal value is quite low, close to 0.1. In phase II, the main shape of structure element is in a monotonous form, which is Laplace wavelet and the complexity is between 0.1 and 0.2. In phase III, the shape of structure element is in bilateral attenuation form, which is Morlet wavelet and the complexity is between 0.2 and 0.3. In stage IV, the main shape of structure element is in the form of twin peaks in one BPFO, which is Morlet wavelet and the complexity is between 0.3 and 0.4. In phase V, the shape of structure element is in variety alternating forms, which leads the complexity sharply to 1 or so, and serious malfunctions appear in this time.

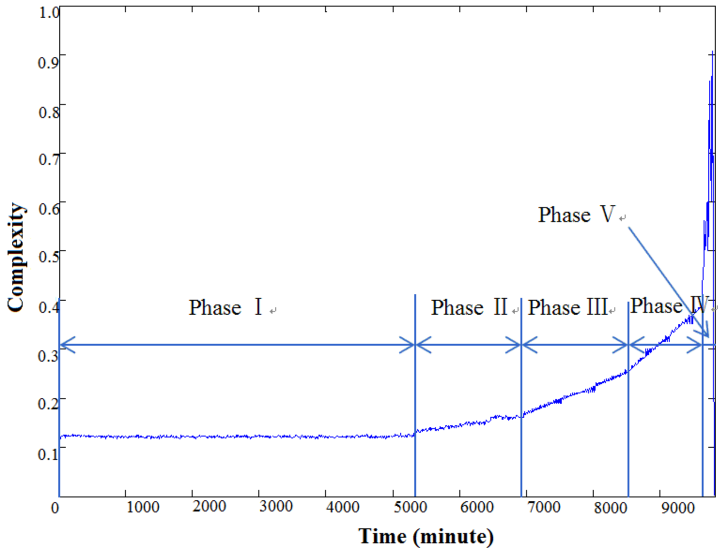
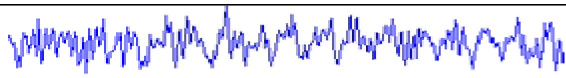
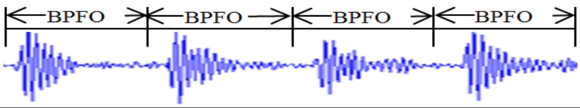
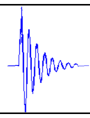
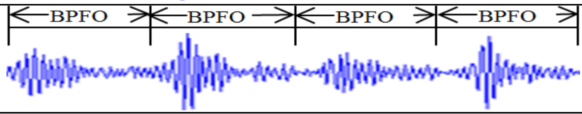
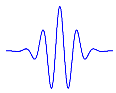
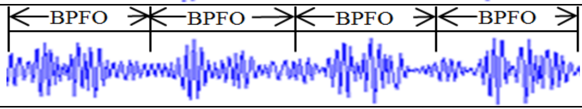
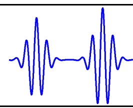
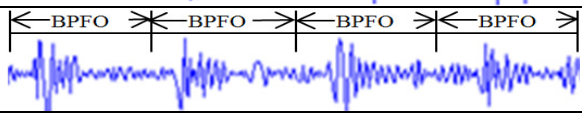


Fig. 11. The Lempel-Ziv complexity feature for the whole life cycle

Table 2. Shape of structure elements in different phases

Phase	Shapes of bearing vibration signals	Shape of structure element
Phase I		–
Phase II		
Phase III		
Phase IV		
Phase V		–

6. Conclusion

Assessing fault severity is one of the main challenges in fault diagnosis. Combining complexity of signal and morphology filtering, this paper proposed a new assessment method for rolling element bearings. So far, the severity is often evaluated on the basis of time-domain or frequency-domain features. Though such indexes may be useful, it is not an easy task to specify a safeguard limit. In addition, the magnitudes of non-relative measures of the signals are dependent on many factors such as bearing size, load, working conditions, as well as the gain used in data acquisition, and also many failures induce no change in the vibration amplitude or other feature index as the fault severity is developed, while the shape of signal waveform and the spectral structure undergoes corresponding changes. Hence, the same signal magnitude does not necessarily indicate the same fault severity and these methods may not provide a reliable indication of fault severity. In order to eliminate this problem, the improved morphological filtering and the revised complexity of signal are adopted to evaluate the fault severity. As shown in this work, the value of complexity is mainly affected by fault severity and should be less susceptible to other factors, the proposed severity measure can be used for rolling element bearings of different sizes under different operation environments, and it has been verified using experimental data. Further research will be mainly concentrated on the validation of the proposed techniques on other rotating machines and other effective criteria for model selection and parameter identification.

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