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On fault feature extraction and diagnosis of rolling bearing under powerful noise

Wei Wang and Yongjian Sun*

School of Electrical Engineering, University of Jinan, Jinan, Shandong, China.

***Corresponding author**
Yongjian Sun, School of Electrical Engineering, University of Jinan, Jinan, Shandong, China.

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Abstract
Rotating machinery is an important equipment in modern industries, which is widely used in aerospace, metallurgy, electricity, mining, railway transportation and other industries. The rolling bearing is widely used in large machinery, especially in rotating machines, such as highly operating precision, low price. The operating status of the rolling bearing is about the safety and reliability of the entire mechanical system, directly affects the overall performance, work efficiency and service life of the equipment. The rolling bearing is one of the most widely used key components in the rotating machine. The harsh working environment leads to its fault, which affects the operation of the entire equipment, which causes the entire production chain to stop production, causing certain economic losses, and the weight is caused Disastrous casualties and serious social hazards. Therefore, the research on the problem of rolling bearing fault diagnosis is carried out, especially for the study of early fault diagnosis and is important for scientific theory and engineering application value. Because the scroll bear generates impact vibration when the scrolling bearing occurs normally or fails, bearing status recognition and fault diagnosis can be achieved by the detection signal containing a fault impact. In order to influence this influence, this paper will study the extraction and diagnosis of the rolling bearing fault characteristics under strong noise conditions, and use the method of extracting sample entropy characteristics on the rolling bearing vibration signal, and is shown in different conditions, and the vibration signal data sample entropy is entropy. The general range and the distribution of its entropy values is expressed by the box line map. In response to noise under different signal-to-noise ratios, the effect of studying its impact on the type of diagnosis of rolling bearing and its change law.

Keywords: Rolling Bearing Fault, Feature signal-To-Noise, Ratio Feature, Extraction troubleshooting entropy Feature

Introduction
Nowadays, with the rapid progress of modern science and technology, promote the development of the machinery industry, a variety of precision large-scale integrated automation, high-speed mechanical equipment emerges in endlessly, the structure of mechanical system is more complex, its scale is also gradually huge. These developments and changes make us need to deal with the design, manufacture, operation and maintenance of mechanical system with higher and more stringent requirements, and also cause the operation of mechanical equipment to be affected by more factors, which improves the potential of mechanical system failure and increases the diversity of fault types, which poses a great challenge to the fault diagnosis of mechanical system. Machinery and equipment are widely used in the current pillar industries of the national economy, such as electric power, petrochemical, transportation and metallurgy [1]. Once a part in the system fails, it may cause chain reaction, reduce production efficiency and affect product quality [2]. More seriously, it will cause casualties, and enterprises will also suffer serious economic losses, which will have a bad impact on society. If we can accurately predict and identify the type of fault when the mechanical equipment just has a weak fault or even when the fault does not occur, we can prevent it from happening, improve the reliability and stability of the mechanical equipment in operation, and more effectively avoid the occurrence of safety accidents [3].

Because rolling bearings generally work in the harsh working environment such as high temperature, high load, dusty and alternating load, and their own poor impact resistance, with the increase of working time, the working conditions of rolling bearings will continue to change, and the surface of parts will appear different degrees and forms of damage, such as deformation, wear, rust, crack and even fracture. As a result, rolling bearing has become one of the most vulnerable parts in mechanical system [4]. Although the value of rolling bearing is not necessarily very high, when it breaks down, it will directly have adverse effects on the shaft and gear parts connected with it, and then affect the whole mechanical system or production line, making it unable to operate normally. The economic loss caused by this is not comparable to the price of a bearing, if it is more serious, it may even lead to equipment damage, causing casualties. It can be seen that rolling bearing is the key factor to determine its stability and reliability in the whole mechanical system, and its normal operation will directly affect the performance of mechanical equipment [5]. According to statistics, nearly 45% of mechanical equipment failures are caused by rolling bearing damage. To sum up, the research is of great significance to the fault condition monitoring, extraction and diagnosis of rolling bearing [6]. Similarly, when we extract and diagnose the fault of rolling bearing, we should also focus on the weak signal generated in the early stage.

But in fact, the actual working environment of rolling bearing is relatively bad, there are all kinds of noises, and the fault signal generated by the bearing in the early fault is very weak, which has a great impact on the early fault feature diagnosis of rolling bearing. Therefore, it is particularly important to study the fault feature extraction and diagnosis of rolling bearing under strong noise conditions, and to seek an effective diagnosis method to provide effective proof for future fault judgment [7].

Fault and data analysis of rolling bearing

Structure of rolling bearing

In order to better study the influence of noise on rolling bearing fault feature extraction and diagnosis, we first understand the structure and fault form of rolling bearing. The main function of rolling bearing is to change the sliding friction between shaft and shaft seat into rolling friction, so as to reduce the friction loss. The typical structure of rolling bearing is shown in figure 1. It can be seen from the figure that the structure of rolling bearing mainly includes inner ring, outer ring, rolling element and cage. Among them, the inner ring mainly rotates with the shaft and cooperates with it; The outer ring plays a supporting role; The rolling elements are distributed between the inner and outer rings and evenly distributed with the help of cages. There are many types of rolling elements, such as ball, cylinder, cone and needle. Different types of rolling elements have different effects on the performance and service life of bearings [8]; The cage makes the rolling force evenly distributed on the track between the inner and outer rings, which plays the role of anti-falling and lubrication.

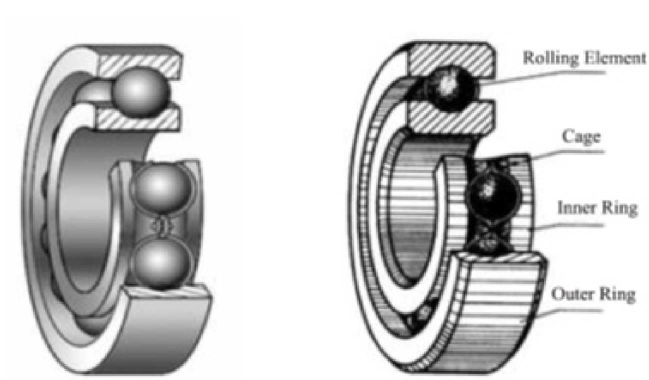

Figure 1: Typical structure diagram of rolling bearing

Fault types of rolling bearing

Due to the complex and harsh working environment of rolling bearing, there aremany fault forms of rolling bearing:

1. Fatigue spalling: due to the special working properties of rolling bearing, the inner and outer ring track and rolling element of the bearing have to bear considerable load. Under the action of these changing loads, small cracks will form under the bearing surface, and the spalling will occur on the bearing surface with the increase of time, and finally develop into a large area of spalling pit. This phenomenon is called fatigue spalling [9].
2. Wear: due to the falling of small and hard objects, the surface of the track and rolling element between the inner and outer rings of the bearing will be worn when the bearing is running, and the lubrication layer will be damaged [10], which further aggravates their wear. As a result, the clearance between various parts of the bearing will be increased, and the smoothness of the surface will be gradually reduced, which will lead to the reduction of the accuracy of the bearing One of the reasons for the increase in noise.
3. Corrosion: This is one of the most serious problems in bearing failure, which is difficult to avoid and solve. It is difficult to prevent all the causes of corrosion, such as moisture, acid, alkaline substances in contact with the components of the bearing, there is a great probability of causing corrosion; Even when it stops running, the moisture in the air will condense the water droplets attached to the bearing surface due to the decrease of bearing temperature, which will also cause the bearing to rust. When the surface of the bearing and the surface of the component body is corroded, the rolling bearing will lose its accuracy and cannot be used normally.
4. Fracture: when the load of the bearing greatly exceeds the rated load [11], the internal parts of the bearing may fracture.
5. Gluing: when the rolling bearing is in high-speed operation, overload and other operating environment for a long time, the parts of the rolling bearing will produce extremely high temperature under the influence of friction. At this time, the temperature can easily burn the surface of the bearing, resulting in gluing between the parts after burning and melting.
6. Plastic deformation: refers to the irrecoverable damage between the inner and outer rings of rolling bearing, such as scratches, dents, etc. The main reasons are too much static load, impact load, extra load caused by deformation due to overheating, foreign matter with high hardness, etc.
7. Cage damage: due to improper installation or operation problems, the cage in the bearing components may be deformed, which may lead to the abnormal operation of the rolling element, aggravate the noise generated by the bearing and damage the bearing.

When the bearing has the above type of fault, it will produce a weak impulse signal in operation. This kind of impact energy can excite the natural frequency vibration of various parts in the system of bearing and bearing seat, and the energy generated by vibration will gradually decrease with the damping of mechanical parts [12]. Because the characteristics of the vibration signals generated by the defects on the inner and outer rings and rolling elements are different, we can also classify the fault types of all rolling bearings into inner ring fault, outer ring fault and rolling element fault [13].

Experimental bearing data

Because the bearing data center of Western Reserve University shared the data collected in an experiment of bearing fault feature detection on the network, the equipment is relatively good, and the experimental equipment is shown in fig.2, which consists of a motor (1.5KW,2HP), torque sensor / decoder, power tester and electronic controller. Therefore, several groups of experimental data under different working conditions will be selected for calculation and research, including normal operation state, inner ring fault, rolling element fault and outer ring fault.

The bearing to be tested is the rolling shaft supporting the motor. The model of the bearing at the driving end is SKF6205. The sampling frequency of the selected data is 12khz. The damage of rolling bearing is a single point damage produced by EDM, with the diameter of 0.1778mm, 0.3556mm and 0.5334mm. The specific specifications and fault frequency of rolling bearing are shown in tab.1 and tab.2. The vibration signal data of rolling bearing under four working conditions including normal state are collected when the motor speed is 1797 r/min, no load, fault specification is 0.1778 mm in diameter and depth is 0.2794 mm.

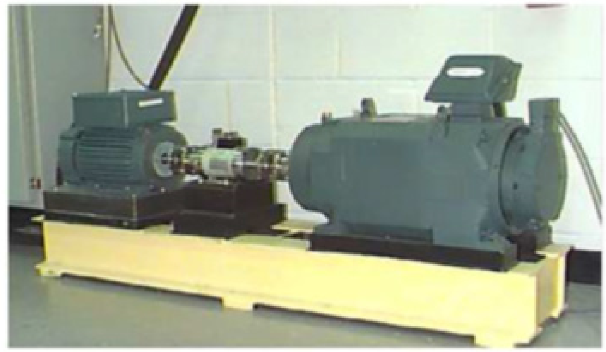

Figure 2: Experimental platform of Western Reserve University

Table 1: Rolling bearing specification

Inner ring fault	Outer ring fault	Thickness	Diameter of rolling element	Pitch diameter
25mm	52mm	15mm	7.94mm	7.94mm 39.04mm

Table 2: Failure frequency of rolling bearing (multiple of rotation frequency Hz)

Inner ring diameter	Outer ring diameter	Cage drum fault	Rolling element failure
5.4152	3.5848	0.39828	4.7135

Research on data processing and diagnosis of rolling bearing

Experimental data processing

In this experiment, we use sample entropy to extract fault features. Sample entropy is a method to measure the complexity of data based on approximate entropy. Compared with approximate entropy, its calculation does not depend on the length of data, and has better consistency. It effectively improves the problem of different calculation results caused by the length of data.

For a time series $\{X_i\} = \{x_1, x_2, \ldots x_N\}$ containing N data, it is arranged into a set of vector sequences with dimension M,m is the given embedding dimension. The m dimensional vectors are obtained as follows:

$$X_m(i) = \{x(i), x(i+1), \ldots x(i+m-1)\},\ i = 1, 2, \ldots N-m \quad (1)$$

These reconstructed m-dimensional vectors represent m consecutive values starting from the i-th point [14].

The distance between $Xm(i)$ and $Xm(j)$ is defined as $d[X_m(i), X_m(j)]$, and $d[X_m(i), X_m(j)]$ is used to represent the absolute value of the maximum difference between the two corresponding elements.

$$d[X_m(i), X_m(j)] = {}_{k=0,1,\ldots m-1}^{max}(|x(i+k)-x(j+k)|) \quad (2)$$

The value of similarity tolerance r is defined. By calculating the distance $d[X_m(i), X_m(j)]$ between $X_m(i)$ and $X_m(j)$, the number B_i less than r is obtained. The relationship between Bi and total N − m − 1 is expressed by $B^m_i(r)$:

$$B_i^m(r) = \frac{B_i}{N-m-1}, 1 \le i \le N-m, i \ne j \quad (3)$$

Calculate the average of $N - m$ $B^m_i(r)$ and repeat the above steps to get $B^m(r)$:

$$B_i^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_i^m \quad (4)$$

Increase the embedding dimension m to $m+1$ and repeat the above steps to get $B^{m+1}(r)$:

$$B_i^{m+1}(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_i^{m+1} \quad (5)$$

Through the above steps, we can get the probability $B^m(r)$ of two sequences matching m points and the probability $B^m(r)$ of matching m+1 points under the similarity tolerance r. therefore, the definition of sample entropy is as follows:

$$SampEn(m,r) = {}_{N\to\infty}^{lim}\{-ln[\frac{B^{m+1}(r)}{B^m}(r)]\} \quad (6)$$

When the amount of data N in the time series is finite, the sample entropy can be estimated by the following formula:

$$SampEn(m,r,N) = -ln[\frac{B^{m+1}(r)}{B^m}(r)] \quad (7)$$

When the bearing fails, due to the periodic impact when the rolling element passes through the fault position, there will be many similar components in the vibration signal sequence, which reduces the value of sample entropy.

Data calculation and processing

The sample entropy is used to calculate the vibration signal data under four working conditions. In order to ensure the accuracy of the results, the bearing data is divided into 110 groups, with 1000 data in each group. The approximate range of the sample entropy of the vibration signal data under each working condition can be obtained by continuous calculation.

Therefore, after compiling the sample entropy calculation algorithm with MATLAB and importing the signal data, the entropy values under each working condition can be obtained as shown in the following table. Due to too much data, only the first 20 groups of data are shown here:

The complete variation range curve of entropy value of calculated samples under each working condition is shown in the figure below:

Table 3: Sample entropy of bearing vibration data in normal Operation

Group	1	2	3	4	5	6	7	8	9	10
Entropy	1.268	1.232	1.274	1.210	1.259	1.278	1.258	1.288	1.257	1.282
Group	11	12	13	14	15	16	17	18	19	20
Entropy	1.308	1.285	1.313	1.261	1.302	1.275	1.285	1.248	1.298	1.261

Table 4: Sample entropy of bearing vibration data with inner ring fault

Group	1	2	3	4	5	6	7	8	9	10
Entropy	1.664	1.569	1.567	1.631	1.634	1.669	1.660	1.647	1.586	1.614
Group	11	12	13	14	15	16	17	18	19	20
Entropy	1.625	1.655	1.609	1.645	1.598	1.607	1.604	1.666	1.627	1.628

Table 5: Sample entropy of bearing vibration data with inner ring fault

Group	1	2	3	4	5	6	7	8	9	10
Entropy	1.980	1.958	1.957	2.000	2.006	2.009	1.969	1.975	1.935	1.989
Group	11	12	13	14	15	16	17	18	19	20
Entropy	1.925	1.972	1.901	2.006	1.962	1.965	1.939	1.998	1.952	1.980

Table 6: Sample entropy of bearing vibration data with outer ring fault

Group	1	2	3	4	5	6	7	8	9	10
Entropy	1.034	1.054	0.983	1.052	0.951	1.019	1.045	1.027	1.003	1.070
Group	11	12	13	14	15	16	17	18	19	20
Entropy	1.028	1.083	1.033	1.054	1.051	1.080	1.031	1.048	1.071	1.074

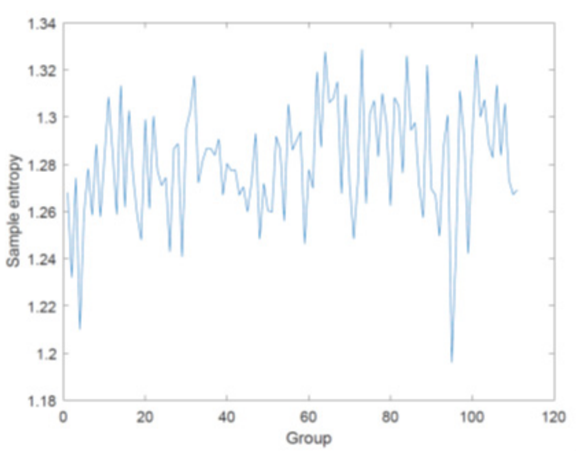

Figure 3: Variation range of sample entropy of bearing vibration data in normal operation

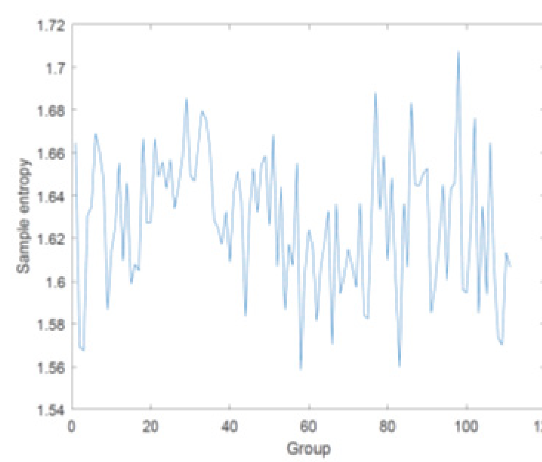

Figure 4: Variation range of sample entropy of bearing vibration data with inner ring fault

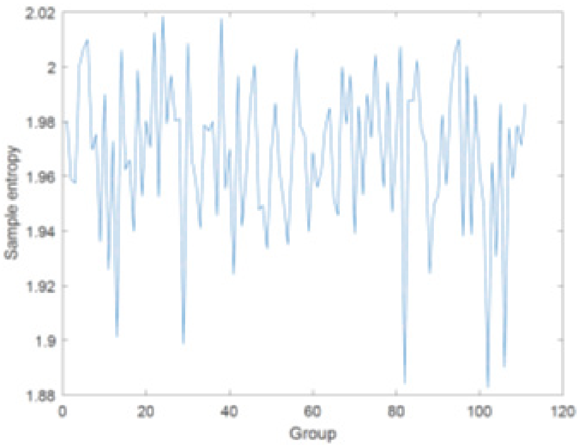

Figure 5: Variation range of sample entropy of bearing vibration data in rolling element fault

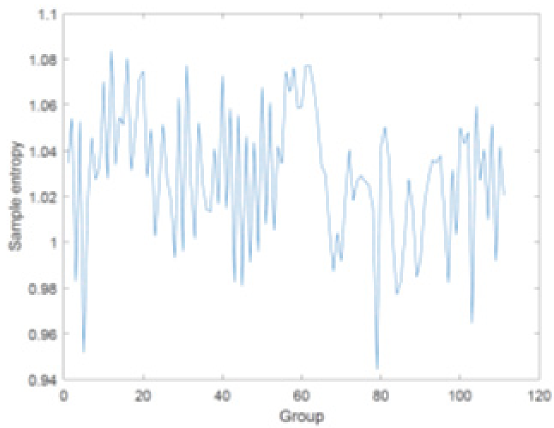

Figure 6: Variation range of sample entropy of bearing vibration data with outer ring fault

According to table 3 and figure 3, the sample entropy of vibration signal data generated when rolling bearing is in normal operation ranges from 1.196 to 1.334.

From table 4 and figure 4, it can be concluded that the sample entropy ranges of vibration signal data generated when rolling bearing inner ring fails is about 1.558 to 1.707. It can be concluded from table 5 and figure 5 that the sample entropy of vibration signal data generated by rolling element fault of rolling bearing ranges from 1.882 to 2.018.

Influence of strong noise on fault feature extraction and diagnosis

Change after adding noise

We can use awgn function in MATLAB to artificially add a group of Gaussian white noise data which can control its signal-to-noise ratio to the bearing vibration signal data under various working conditions. Then calculate the sample entropy, Under the influence of different signal-to-noise ratio, the influence and change trend of fault feature extraction and diagnosis for each working condition are observed.

After adding noise, the influence of different signal-to-noise ratio (SNR; Unit: dB) on the sample entropy range under various conditions is shown in the following table: Through the above four tables, it is not difficult to find that when the signal-to-noise ratio of noise is greater than or equal to 50dB, the influence of noise on the sample entropy of rolling bearing vibration signal is negligible. We focus on the effect of noise below 50 dB. Their box line diagram is as follows:

Table 7: Entropy range under different SNR in normal operation (unit: dB)

SNR	No noise	10	20	30	40	50	60	70
Upper limit	1.334	1.997	1.969	1.665	1.404	1.336	1.334	1.332
Lower limit	1.196	1.912	1.872	1.522	1.264	1.212	1.197	1.194
Mean value	1.281	1.964	1.921	1.608	1.351	1.289	1.281	1.281

Table 8: Entropy range under different SNR in case of inner ring fault (unit: dB)

SNR	No noise	10	20	30	40	50	60	70
Upper limit	1.707	1.967	.796	1.720	1710	1.705	1.706	1.706
Lower limit	1.558	1.844	1.667	1.559	1.561	1.557	1.560	1.194
Mean value	1.627	1.913	1.724	.642	1.629	1.627	1.627	1.627

Table 9: Entropy range of rolling element fault under different SNR (unit: dB)

SNR	No noise	10	20	30	40	50	60	70
Upper limit	2.018	2.109	2.099	2.033	2.021	2.015	2.017	2.017
Lower limit	1.882	2.032	2.025	1.908	1.877	1.884	1.882	1.882
Mean value	1.968	2.071	2.059	1.979	1.968	1.968	1.968	1.968

Table 10: Entropy range under different SNR when outer ring fault occurs (unit: dB)

SNR	No noise	10	20	30	40	50	60	70
Upper limit	1.083	1.615	1.207	1.103	1.085	1.084	1.083	1.083
Lower limit	0.944	1.412	1.053	0.963	0.948	0.944	0.944	0.944
Mean value	1.029	1.511	1.124	1.041	1.031	1.029	1.029	1.029

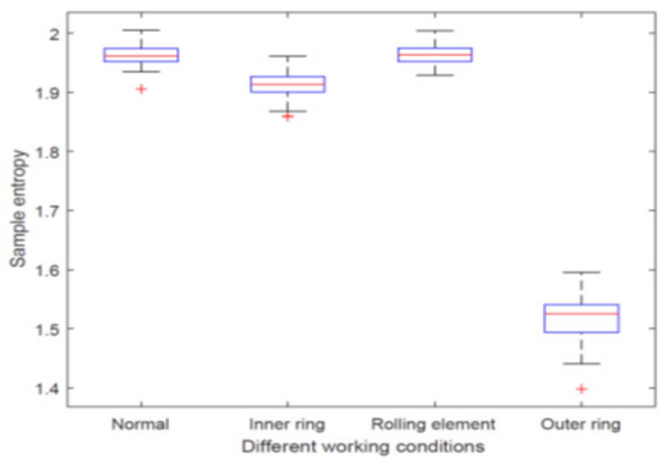

Figure 7: Box plot of sample entropy under different working conditions when SNR is 10dB

Impact analysis

Through the research on the influence of noise on the accuracy of rolling bearing fault diagnosis under different signal-to-noise ratio, it can be found that when the signal-to-noise ratio is too low, that is, when the power ratio of noise is too high; it has a great influence on the accuracy of fault diagnosis. In this case, we cannot judge which kind of fault causes the fault characteristics at this time. With the improvement of signal-to-noise ratio (SNR), that is, the proportion of noise decreases, the accuracy of fault diagnosis is also improving. When SNR is equal to or greater than 50dB, the influence of noise on the accuracy of fault diagnosis has been relatively low or even no influence, and the noise is basically out of the category of strong noise.

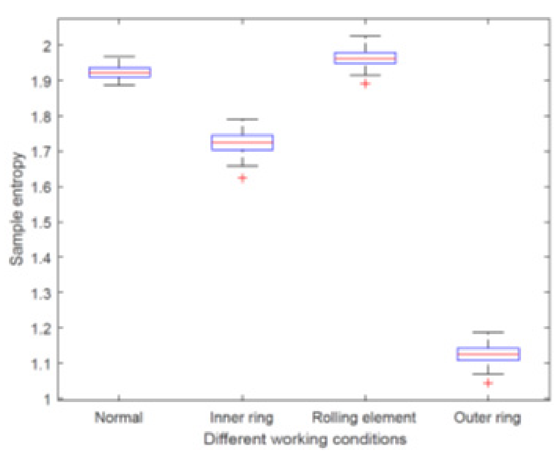

Figure 8: Box plot of sample entropy under each working condition when SNR is 20dB

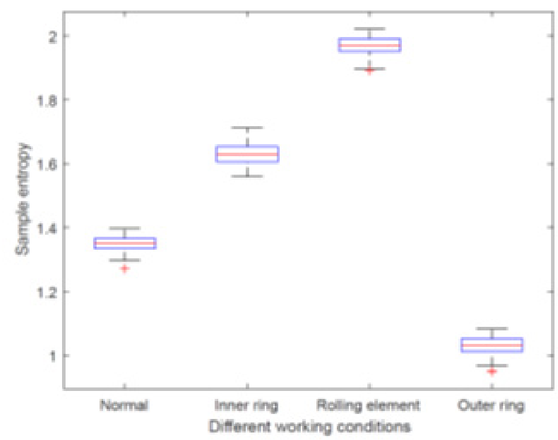

Figure 9: Box plot of sample entropy under each working condition when SNR is 30dB

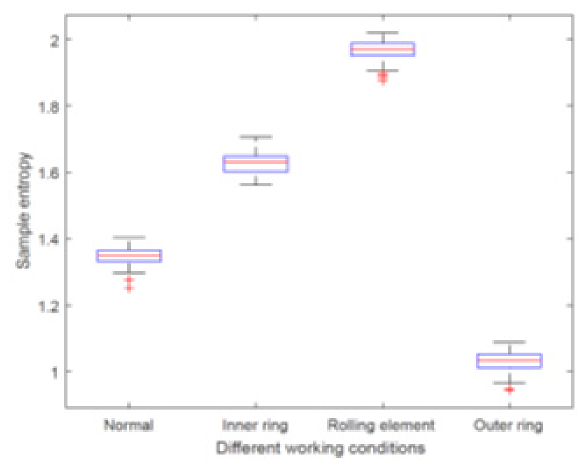

Figure 10: Box plot of sample entropy under each working condition when SNR is 40dB

Through the research on the influence of noise on the accuracy of rolling bearing fault diagnosis under different signal-to-noise ratio, it can be found that when the signal-to- noise ratio is too low, that is, when the power ratio of noise is too high, it has a great influence on the accuracy of fault diagnosis. In this case, we cannot judge which kind of fault causes the fault characteristics at this time. With the improvement of signal-to-noise ratio (SNR), that is, the proportion of noise decreases, the accuracy of fault diagnosis is also improving. When SNR is equal to or greater than 50dB, the influence of noise on the accuracy of fault diagnosis has been relatively low or even no influence, and the noise is basically out of the category of strong noise

Conclusion

Rolling bearing is the core of rotating machinery system and the "joint" of modern industry. As an indispensable part of the mechanical equipment and system, its good or bad determines the good or bad of the mechanical equipment to a certain extent, it is very necessary to detect the fault of rolling bearing. In the development process of so many years, scholars have developed a variety of methods that can effectively detect the fault of rolling bearing. At the same time, more people have carried out research and innovation on this basis, and strive to do better. In this experiment, the vibration signal data of rolling bearing is extracted by using the calculation method of sample entropy. At the same time, in order to ensure the accuracy of the calculation results, the rolling bearing fault experimental data published by Western Reserve University is used to select a group of data under each working condition, and the bearing vibration data is divided into 110 groups, with 1000 data in each group. After cyclic calculation of these data, the approximate range of sample entropy under each working condition is obtained, which can be used as the criteria for feature extraction and diagnosis of rolling bearing fault under strong noise. The awgn function is used to add Gaussian white noise which can control the signal-to-noise ratio to the original bearing vibration signal data, and the sample entropy of the new rolling bearing vibration signal data with noise data is calculated again. According to the same steps, the sample entropy ranges of each working condition under different signal-to-noise ratios can be calculated, that is, when the noise is low, its impact on fault diagnosis is very weak. When the signal-to-noise ratio is lower than 10dB, the noise interference on fault diagnosis is very strong. At this time, we cannot even make normal and accurate fault diagnosis. Between 10dB and 50dB, the impact of noise on Fault Diagnosis will gradually weaken until the impact becomes negligible.

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