Bearing Fault Diagnosis Based on Chaotic Dynamic Errors in Key Components

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ABSTRACT Ball bearings are one of the most common components used in rotating machines. They reduce the rotational friction between the shaft and fixed components and maintain the center line of rotation of the shaft. A damaged bearing will cause abnormal vibration and noise, and often results in machine failure and loss of production. In this study the public database on ball bearings, provided by the Vibration Institute of Machinery Failure Prevention Technology (MFPT), was used for data retrieval and analysis, and a diagnosis model was created according to the data sets of the bearing in the database. Three different approaches were used for the extraction of features and a classifier was used to implement a diagnostic system. The aim of this study was a comparison of three approaches. The first was the Short-time Fourier Transform (STFT) where the time-frequency domain image is extracted as the feature used for status identification. The second and third approaches were based on the Chen-Lee Chaotic and the Lorenz Chaotic Systems and chaotic dynamic error maps were used in analysis and feature status identification. Chaotic systems are particularly sensitive to the slightest changes in input signals, and the time domain signals from bearings in different conditions were mapped onto individual images. The feature images extracted by the three different approaches were then used for training and verification in a Convolutional Neural Network (CNN). From the results of the experiments, it can be seen that all three approaches gave high identification rates. The interactive verification identification rate of the Chen-Lee chaotic system with CNN under three statuses reached 98.33%, and it also had the best computational efficiency in the condition without losing any classification accuracy. This will make a substantial contribution to real-time ball bearing fault diagnosis.

INDEX TERMS Ball bearing fault detection, convolutional neural network, short-time Fourier transform, Chen-Lee chaotic system, Lorenz chaotic system.

I. INTRODUCTION

Ball bearings have three main components, an outer race, an inner race and balls, as shown in FIGURE 1. They are essential components in all rotating machinery. They have less rotational friction and generate less heat than other types of mechanical bearing. A bearing in good condition will keep the shafts and rotating parts in centric alignment with each other and prevent the development of eccentricity. A faulty bearing will affect the performance of the machine and result in poor production quality and often stop production altogether while repair is being made. It is very important to be able to effectively detect developing ball bearing faults and to implement an early warning and maintenance mechanism to reduce the losses caused by bearing failure. The inner or outer races of ball bearings operated under heavy load and at high speed may suffer deformation from wear. Therefore, more attention should be paid to monitoring the status and to the diagnosis of faults in ball bearings in operation. However, the analytical results of ball bearing fault diagnosis are difficult to categorize because an evaluation standard for real-time diagnosis has not yet been established. Although the evaluation of the status of ball bearings, conducted according to the current industrial standards stipulated by the ISO [1],

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makes the definition of ball bearing damage clearer, it does not yet do so for a real-time situation. As for the bearing status diagnosis technology, some research has been done that emphasizes bearing status with reference to stator current under variable load [2]–[4], but this physical measurement does not clearly highlight characteristic details. Some work has been done on methods that utilize the measurement of the frequency of sounds generated during the operation of bearing as a detection feature [5], [6], however, environmental noise during machine operation is usually much higher than bearing noise and this limits the application. Other studies have used abnormal variations in temperatures of the bearing as a feature [7], and here the critical issue is whether the temperature sensor can measure the actual temperature of the bearing. Most of the research work done has therefore been on measurement of the changes in vibrations generated by running bearings [8]–[10]. However, the data collected from a vibrating bearing is often mixed with a lot of external noise and it is also not easy to decide if the damage is present in the inner race, the outer race or the balls themselves. Therefore, the realization of an effective diagnostic system requires the extraction and analysis of vibration signal features. Most of the processing approaches have been based on the transformation of time domain signals into frequency domain signals for the determination of spectral value. The current main signal processing approaches are based on the Fast Fourier Transform (FFT) [11]–[14] and Wavelet Transform [15]–[18] for feature extraction. However, the Fourier Transform signal mapping feature is limited to non-stationary time-variance and cannot accurately describe the local signal characteristics. It is also difficult to conduct real-time processing using the wavelet transform due to the huge computational load. It is clear that an efficient and accurate signal pre-processing method is a prerequisite for the advancement of this technology. However, artificial intelligence has once again become a hot topic as a result of the huge increase in computing power now available. The AI related model [19]–[22] and technology such as the Artificial Neural Network (ANN) have become the subject of much intense research.

In this present study features have been extracted from the ball bearing fault signals provided by the Machinery Failure Prevention Technology (MFPT) with the data prepared by Dr. Eric Bechhoefer (https://www.mfpt.org/fault-data-sets/) [23] using three different methods. This dataset includes data from the bearing testing stand (baseline bearing data, outer race failure under various loads, inner race failure under various loads) and three actual failures. In the first an analysis of vibration signals was conducted using Short-time Fourier Transform (STFT) [24], [25] and a model was constructed from the frequency domain images using CNN. In the second and third methods analyses of vibration signals through the chaotic system [26]–[31] were conducted and the chaotic dynamic error maps obtained were used for feature images and the construction of models using CNN [32]–[34]. A comparison of the accuracy rate and efficiency in each of these three approaches was then conducted.

### II. EQUIPMENT AND EXPERIMENTAL

The ball bearing signals provided by MFPT used in the study are as shown in TABLE 1, and the specifications of the bearing are shown in TABLE 2. The bearings were developed and produced by RBC Bearings Incorporated and the sampling frequency of the vibration signals in the database were 97,656 Hz and 48,828 Hz, respectively. The detailed description of the bearing faults is as shown in TABLE 3. This includes normal load status, fault load status of the outer race, and fault load status of the inner race. The PC hardware facility used for analysis and identification in this study included an Intel (R) Core (TM) i7-7700 CPU 3.60GHz, 16GB of RAM, and an NVIDIA GeForce GTX-1050Ti graphics card. Software was: Matlab 2019a, Machine Learning Toolbox 11.5, Deep Learning Toolbox 12.1, and the Neural Network Training Toolbox.

The experimental flowchart for the study is shown in FIGURE 2. First, 36 records are made at 48,828 Hz of bearings with normal operation status as shown in TABLE 4, the signals were all recorded for the same length of time. A model was created using CNN from data extracted by STFT, and the Chen-Lee Chaotic and Lorenz Chaotic Systems [35]–[37].

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**TABLE 1. The original signal data from the database.**

| Status          | Sampling frequency (Hz) | Sampling time (s) | Length of data points | Number of data records |
|-----------------|-------------------------|-------------------|-----------------------|------------------------|
| Normal Status   | 97,656                  | 6                 | 585,936               | 3                      |
| Outer Race Fault| 48,828                  | 3                 | 146,484               | 7                      |
| Inner Race Fault| 48,828                  | 3                 | 146,484               | 7                      |

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**TABLE 2. Bearing parameters.**

| Type                | Parameter                  |
|---------------------|----------------------------|
| Roller diameter     | 0.235 (Inch)              |
| Pitch diameter      | 1.245 (Inch)              |
| Number of Elements  | 8                          |
| Contact Angle       | 0°                         |
TABLE 3. Types of ball bearing failure.

| Type                  | Parameter               |
|-----------------------|-------------------------|
| Sampling frequency    | 97,656/48,828 (Hz)      |
| Load: Normal Status   | 270 (lbs)               |
| Load: outer race fault| 25/50/100/150/200/250/300 (lbs) |
| Load: inner race fault| 0/50/100/150/200/250/300 (lbs) |

TABLE 4. Signal data after preprocessing.

| Status       | Sampling frequency (Hz) | Length of data points | Number of data records |
|--------------|-------------------------|-----------------------|------------------------|
| Normal Status| 48,828                  | 48,828                | 36                     |
| Outer Race Fault | 48,828              | 48,828                | 21                     |
| Inner Race Fault | 48,828              | 48,828                | 21                     |

FIGURE 2. Flowchart of the experiment.

After this a comparison was made of each approach to find which gave the best accuracy rate and efficiency.

III. SHORT-TIME FOURIER TRANSFORM

The process methods used in most previous studies have focused on the discussion of spectral values after using FFT to find the feature frequency band of the signals. However, it is only possible to obtain one complete signal segment using FFT. This will include the content of the frequency of non-stationary time-variant signals, but will have no information about the time of appearance of each component. Two signals with large difference in time domain may result in a similar spectrum diagram. FIGURE 3 (a) and (c) show time series signals where the frequency is in the order of 30Hz, 60Hz, 90Hz, and 90Hz, 60Hz, 30Hz, and the frequency spectrum obtained after FFT is as shown in FIGURE 3 (b) and (d). It is not difficult to see the trend of frequency changes over the time period from the characteristics of the frequency spectrum. The short-time Fourier transform decomposes the entire process of time series into several small processes with equal length using the Window function, so that a more comprehensive understanding of the variation status of frequency over the time period becomes possible. The Fourier transform was done for each box area of the Window Function respectively to find out the relationship between time and frequency, as shown in FIGURE 4.

The STFT has low computational complexity and linear distribution functions and it does not result in cross terms. It is often used to analyze non-steady and time-variant signals. Its definition is as shown in (1) [38], [39].

\[
STFT(t, f) = \int_{-\infty}^{+\infty} x(\tau) \omega(t - \tau)e^{-j2\pi f \tau} d\tau
\]

where \(\omega(t - \tau)\) is the Windows function and \(x(\tau)\) is the signal to be transformed, and \(STFT(t, f)\) is the Fourier transform of \(x(\tau)\omega(t - \tau)\) with the changes in time \(t\); the windows function will shift on the time axis. In this study the Hamming window [40] was used as the STFT function, with a windows length of 100.

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The Chen-Lee dynamic equation is as shown in (2) [29].

\[
\begin{align*}
\dot{x} &= -\gamma z + \alpha x \\
\dot{y} &= xz + \beta y \\
\dot{z} &= \frac{1}{3} xy + \gamma z 
\end{align*}
\]  

(2)

To obtain the dynamic error of the Chen Lee chaotic system, the above equation can be rewritten in the form of a nominal system and a test system, as shown in (3) and (4).

\[
\begin{align*}
\dot{x}_m &= -y_m z_m + \alpha x_m \\
\dot{y}_m &= x_m z_m + \beta y_m \\
\dot{z}_m &= \frac{1}{3} x_m y_m + \gamma z_m \\
\dot{x}_s &= -y_s z_s + \alpha x_s \\
\dot{y}_s &= x_s z_s + \beta y_s \\
\dot{z}_s &= \frac{1}{3} x_s y_s + \gamma z_s 
\end{align*}
\]  

(3)

(4)

The dynamic error of the system is obtained by the subtraction between the nominal system and the test system. To facilitate the subtraction of the two systems, the above two formulas are rewritten in matrix form for the computation, as shown in (5) and (6) [37], [41].

\[
\begin{bmatrix}
\dot{x}_m \\
\dot{y}_m \\
\dot{z}_m
\end{bmatrix} =
\begin{bmatrix}
\alpha & 0 & -y_m \\
0 & \beta & x_m \\
\frac{1}{3} & \gamma & \frac{1}{3}
\end{bmatrix}
\begin{bmatrix}
x_m \\
y_m \\
z_m
\end{bmatrix}
\]  

(5)

\[
\begin{bmatrix}
\dot{x}_s \\
\dot{y}_s \\
\dot{z}_s
\end{bmatrix} =
\begin{bmatrix}
\alpha & 0 & -y_s \\
0 & \beta & x_s \\
\frac{1}{3} & \gamma & \frac{1}{3}
\end{bmatrix}
\begin{bmatrix}
x_s \\
y_s \\
z_s
\end{bmatrix}
\]  

(6)

In this study the concept of Digital Signal Processing is introduced and the input signals of the system can be defined as a nominal system and test system respectively, as shown in formula 7 and 8 [42].

\[
n[i] = [n[1], n[2], n[3] \cdots n[i]]
\]  

(7)

\[
t[i] = [t[1], t[2], t[3] \cdots t[i]]
\]  

(8)

Both formula (7) and (8) are digital vibration signals with length of \(i\), so the parameters of the nominal system in formula (5) can be defined as \(x_m[i] = n[i + 1], y_m[i] = n[i + 2]\), and \(z_m[i] = n[i + 3]\) based on the above definition; and the parameters of test system in formula (6) can be defined as \(x_s[i] = t[i + 1], y_s[i] = t[i + 2]\), and \(z_s[i] = t[i + 3]\) so that the chaos system can perform digital signal processing [43]. On the basis of the definition of a chaos system, the dynamic error of the system can be obtained by subtracting formula (5) and (6) and the dynamic error equation of the chaos system can be expressed by formula (9).

\[
\begin{bmatrix}
\dot{e}_1[i] \\
\dot{e}_2[i] \\
\dot{e}_3[i]
\end{bmatrix} =
\begin{bmatrix}
\alpha & 0 & 0 \\
0 & \beta & 0 \\
0 & 0 & \gamma
\end{bmatrix}
\begin{bmatrix}
e_1[i] \\
e_2[i] \\
e_3[i]
\end{bmatrix} +
\begin{bmatrix}
-e_2 e_3 \\
e_1 e_3 \\
-\frac{1}{3} e_1 e_2
\end{bmatrix}
\]  

(9)

where \(e_1[i] = x_m[i] - x_s[i], e_2[i] = y_m[i] - y_s[i], \) and \(e_3[i] = z_m[i] - z_s[i]\) in the above formula, if \(\alpha, \beta, \) and \(\gamma\) are the system parameters and that \(\alpha > 0, \beta < 0\) and \(0 < \alpha < (-\beta + \gamma)\), then the system will be sure to have the characteristics of strange attractor. Therefore, Particle Swarm Optimization (PSO) was used to find the best parameters for the system; the three parameters \(\alpha, \beta, \) and \(\gamma\) can be calculated by iteration in PSO; the chaotic nonlinear feature mapping can be performed using the system parameters obtained by each iteration, and
the mapped features can then be substituted into the CNN for model training. The smallest CNN classification error is used as the objective function and if the classification error is less than 0.001, it converges to give the best parameters for Chen-Lee chaotic system. PSO can be defined as follows:

\[
V_i(t) = W \times V_i \times (t - 1) + C_1 \times \text{Rand} \times (P_{\text{best}} - X_i) + C_2 \times \text{Rand} \times (G_{\text{best}} - X_i) \tag{10}
\]

where \(V_i\) is the velocity of each particle; \(i\) is the number of the particle; \(W\) is the inertia weight; \(C_1\) and \(C_2\) are the learning constants; \(\text{Rand}\) is a randomly generated number between 0 and 1; \(P_{\text{best}}\) is the best solution for each particle as of now; \(G_{\text{best}}\) is the best solution for all particles as of now; \(X_i\) is the location of each particle. Where the PSO location update formula is:

\[
X_i(t) = X_i(t - 1) + V_i(t) \tag{11}
\]

PSO was used to search for the best parameters for the Chen-Lee chaotic system. FIGURE 6 demonstrates the PSO iteration process. It can be seen from the figure below that the system parameters are \(\alpha=2, \beta=-4, \gamma = 3\) by the 76th iteration of PSO. The classification error of the CNN can be reduced, using the mapped characteristics of the system parameters, to lower than 0.001 to make PSO converge to give the best solution. This facilitates subsequent signal feature extraction using system parameters.

V. LORENZ CHAOTIC SYSTEM

This section focuses on the discussion of the Lorenz chaotic system, which was proposed by Edward Norton Lorenz in the 1950s. It is significantly important to nonlinear systems and uses the methods described in section IV for feature identification. The Lorenz dynamic equation is shown in (12).

\[
\begin{align*}
\dot{x} &= \alpha(y - x) \\
\dot{y} &= x(\beta - z) - y \\
\dot{z} &= xy - yz
\end{align*} \tag{12}
\]

To obtain the dynamic error of the Lorenz chaotic system, the above formula can be rewritten in the form of a nominal and an actual test system, as shown in (13) and (14):

\[
\begin{align*}
\dot{x}_m &= \alpha(y_m - x_m) \\
\dot{y}_m &= x_m(\beta - z_m) - y_m \\
\dot{z}_m &= x_my_m - \gamma z_m \\
\dot{x} &= \alpha(y - x) \\
\dot{y} &= x(\beta - z) - y \\
\dot{z} &= xy - yz
\end{align*} \tag{13}
\]

They can be rewritten in matrix form to facilitate the subsequent subtraction as shown in (15) and (16).

\[
\begin{bmatrix}
x_m \\ y_m \\ z_m \\ x_s \\ y_s \\ z_s
\end{bmatrix} =
\begin{bmatrix}
\alpha & \alpha & 0 & 0 & 0 & 0 \\
\beta & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & -\gamma & 0 & 0 & 0 \\
\end{bmatrix}
\begin{bmatrix}
x_m \\ y_m \\ z_m \\ x_s \\ y_s \\ z_s
\end{bmatrix} \tag{15}
\]

\[
\begin{bmatrix}
\dot{e}_1[i] \\ \dot{e}_2[i] \\ \dot{e}_3[i]
\end{bmatrix} =
\begin{bmatrix}
\alpha & \alpha & 0 & e_1[i] & 0 & 0 \\
\beta & -1 & 0 & 0 & e_2[i] & 0 \\
0 & 0 & -\gamma & 0 & 0 & e_3[i] \\
\end{bmatrix} +
\begin{bmatrix}
0 \\ 0 \\ -e_1 e_3
\end{bmatrix} \tag{17}
\]

VI. CONVOLUTIONAL NEURAL NETWORK

In this study the Chen-Lee Chaotic System, Lorenz Chaotic System, and STFT were used for feature extraction. These approaches were used to convert one-dimensional time series signals into feature images. Signal features were extracted from these images which were then classified and diagnosed using the Convolutional Neural Network (CNN). The CNN is a high performance in-depth learning network used for image processing. It conducts feature extraction on the original images through several convolution layers, a pooling layer, and activation functions, and then substitutes the obtained feature map into the fully connected layer for the back-propagation algorithm [44]–[48]. A convolutional neural network is composed of an input layer, a convolution layer, a pooling layer, an activation layer, a fully connected layer, and an output layer [49]. The convolutional neural network structure designed in this paper is as shown in FIGURE 7. The convolutional layer analyzes the local area of images through a spatial filter and maps the extracted features to the
next layer. However, to effectively reduce the size of the feature image with minimal impact on the feature value, the max pooling layer [50] or average pooling layer [51] is usually applied after the convolutional extraction of features, which greatly improves the computational efficiency of the entire network. To prevent the issue of gradient loss or gradient explosion, an activation layer is usually placed in the network structure for non-linear transformation of the features obtained from the previous layer. The commonly seen activation functions include Sigmoid formula (18) and ReLU formula (19). The issue of gradient loss is easier to achieve with the Sigmoid, and the output of ReLU is relatively stable [52]. In this study the max pooling and ReLU were selected as the study parameter to retain the strongest image feature, prevent the occurrence of gradient loss, and speed up computation.

\[ f(x) = \frac{1}{1 - e^{-x}} \]  
(18)

\[ f(x) = \begin{cases} 
0 & \text{for} \ x < 0 \\
 x & \text{for} \ x \geq 0 
\end{cases} \]  
(19)

VII. RESULTS AND DISCUSSION

A. STFT FEATURE EXTRACTION RESULTS

The effective reduction of signal dimension and the mapping of features with high correlation is a very important task essential to the enhancement, training and classification efficiency of the model. On the basis of the signal data proposed by MFPT, original signals from ball bearing vibrations in normal status, and with outer race and inner race faults, as shown in FIGURE 8 (a) to (c), were subject to time-domain and frequency-domain conversion using the STFT. The feature band from each different bearing condition can be determined by the frequency-domain response diagram, as shown in FIGURE 9 (a) to (c).

FIGURE 9 is a frequency-domain response diagram of vibration signals after STFT analysis. It can be seen that the instantaneous frequency of vibrations from bearings in different condition, normal, with outer race or inner race faults are different at different time intervals. This means the status of bearing can be identified using the time-frequency response diagram, to facilitate the training efficiency of the CNN model as well as its classification identification rate.

B. THE CHEN-LEE CHAOTIC SYSTEM NONLINEAR FEATURE MAPPING RESULTS

The second approach to signal preprocessing used in this study was made using the Chen-Lee chaotic system. Chaos systems are extremely sensitive to small changes in input signal and this characteristic was used to highlight the differences between the time domain vibration signals from bearings in different condition (status). In this section, the time domain vibration signals of the three statuses in FIGURE 8 were used to conduct nonlinear feature mapping as shown in FIGURE 10.

FIGURE 10 shows the dynamic error distribution diagram of the Chen-Lee chaotic system, (a) from a bearing in normal status, Figure (b) from a bearing with an outer race fault and
Figure (c) from a bearing with an inner race fault. The chaotic distribution in the diagrams is also compared and was found to be the most divergent for inner race faults and least in a normal bearing. The differences are obvious and significant and the use of this method for diagnosis is clearly useful.

C. THE LORENZ CHAOTIC SYSTEM NONLINEAR FEATURE MAPPING RESULTS

This section focuses on the Lorenz chaotic system which is similar to the Chen-Lee system discussed in Section IV. The Lorenz chaotic system is extremely sensitive to variations in the input signal and this characteristic was used to highlight the differences between time-domain vibration signals from bearings in normal and faulty condition as before. The time domain signals of the three statuses in FIGURE 8 were used to conduct the nonlinear feature mapping through the Lorenz chaotic system, as shown in FIGURE 11.

It can be seen from FIGURE 11 that the bearing status can be clearly identified by observing the chaotic distribution, which is similar to that seen in the Chen-Lee system. It is clear that the Lorenz method can also facilitate the training efficiency of the CNN model as well as its classification identification rate.

D. COMPARISON OF THE CNN IDENTIFICATION RESULTS AND OTHER CLASSIFICATION MODELS

The main contribution made by this study was the establishment of an artificial intelligence ball bearing fault diagnosis system that is efficient and robust. The signal preprocessing is most important after which comes the preparation of a classification model. Three signal processing methods were examined to obtain their features, and the convolutional neural network was applied for training and testing to determine the time spent on data signal processing in each case, as well as the difference in cross-validation identification.

TABLE 5 and TABLE 6 displays the results of the experiments and it can be seen that the chaos system is more efficient than STFT, taking only 0.05 second for feature extraction. Furthermore, the robust nonlinear feature mapping capability of the chaos system gives a very high identification rate with a shallower convolutional neural network layer. Its accuracy rate reached 98.33%, which was the best of the three methods.

VIII. CONCLUSION

In this paper, three approaches for processing public data sets of ball bearing vibrations under different condition (status) provided by the Vibration Institute of the Machinery Failure Prevention Technology are presented. The differences
between the chaos systems and the common time domain to frequency domain approach are discussed. The convolutional neural network was also applied for classification and comparison of classification performance and efficiency was conducted. On the basis of the final results, both the Chen-Lee Chaotic and Lorenz Chaotic Systems could separate the features of ball bearing vibration signals and both had excellent nonlinear mapping capability. It was found that the Chen-Lee Chaotic System was even more suitable for application in power machinery systems according to previous published research and reached a classification accuracy of 98.33% with the CNN, which was the highest of the three. The signal processing calculations used in the Chen-Lee and Lorenz systems were also relatively simple and took only 0.05 second to complete. Although the STFT with CNN is a commonly used method and the experiments showed insignificant difference in time-frequency calculations using vibration data from faulty bearings, the identification rate was slightly lower than in the chaos Systems. Furthermore, the STFT computation, conducted through the Window function, is more complicated and takes longer to extract features. This makes it less efficient than the chaos systems. The Chen-Lee Chaotic System is clearly the preferred method and has high classification and computational efficiency. It also had the highest rate of identification at 98.33% and the shortest signal processing time of 0.05 second. In the light of the excellent results achieved, more analyses will be done on more diverse ball bearing data sets and the Chen-Lee Chaotic System will be used as an embedded system for the development of a convenient real-time bearing fault diagnosis system.

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