Modeling and Intelligent Identification of Axis Orbit for Rotating Machinery Based on the Convolution Neural Networks

Xiaofeng He¹, Xiaofeng Liu¹, Xiulian Lu¹, Lipeng He¹, Yunxiang Ma¹, Sheng Guo² and Tao Yang²,*

¹Jiangsu Frontier Electric Technologies Co., Ltd., Nanjing, 211102, China
²School of Energy and Power Engineering, Huazhong University of Science & Technology, Wuhan, 430074, China

*Corresponding author email: hust_yt@hust.edu.cn

Abstract. Based on the high dimensional complex feature recognition capability of convolutional neural networks (CNN), this paper proposes a method for orbit intelligent identification of rotating machinery based on CNN. In this method, the orbit is purified based on the frequency-domain filtering algorithm. Then an algorithm for converting the vibration signal to the orbit matrix is proposed to construct the input matrix of CNN. Finally the classification model of the CNN is established to realize the automatic identification of the orbit of rotating machines. Case studies show that the proposed method has high identification accuracy over 85% on experimental data and good universality over 73% in field data identification.

1. Introduction

With the continuous improvement of the technical level and complexity of rotating machinery, the operating conditions of which become increasingly complex and changeable. If a fault occurs, it will cause unexpected shutdown of rotating machinery, which may cause huge economic losses and safety accidents. The purpose of rotating machinery fault diagnosis is to detect and identify the fault before its deterioration, which is very important to ensure the safe and reliable operation of large-scale rotating machinery [1]. In recent years, with the increasing demand for intelligent control and management in industry, production operators need to master the operation status and health of the equipment in real time, which results in a rising requirements for intelligent fault diagnosis of rotating machinery.

At present, the fault diagnosis methods based on machine learning takes vibration data as input and outputs equipment fault conditions directly, which can achieve intelligent fault diagnosis [2-3]. As the latest research achievement in the field of machine learning, deep learning (DL) that can represent abstract attribute features and avoid the complex feature extraction process has been applied in the field of rotating machinery fault diagnosis [4-6]. Although DL based diagnosis methods have good accuracy for experimental data diagnosis, the generality of which is poor. When the DL model trained by specific equipment data is used to diagnose equipment with similar structure, it cannot get good results due to the difference in data characteristic distribution, noise and operating conditions. Expert system is an intelligent system with the ability to solve problems in expert level, which is mainly composed of human-machine interface, knowledge base, inference engine and interpreter [7-8]. Expert system contains many domain expert knowledge and can imitate the thinking of human experts...
to solve problems by logical reasoning, which is the optimal choice to solve the universality of fault diagnosis model. Li Yu [9] introduced semantic ontology technology into knowledge representation of fault diagnosis, and built an expert system for steam turbine generator set combining with ontology and case-based reasoning. Li Yun [10] built a large wind turbine fault diagnosis expert system through two parts: fault symptom extraction and expert system.

Axis orbit is an important symptom in fault diagnosis expert system for rotating machinery, which is very critical to judge the running state of rotors [11] [12] and requires professional knowledge to identify its shape accurately. In recent years, scholars have proposed some intelligent identification methods for the shape of axis orbit. Xu Jiarui [13] used wavelet transform to purify the axis orbit, and combined moment invariants and support vector machine (SVM) to identify the shape of axis orbit. Yuan Xlai et al. [14] used the improved moment invariants algorithm to extract the characteristics of the rotor axis orbit of hydropower units under different operating conditions, and constructed a probabilistic neural network (PNN) for classification. Shao Jie et al. [15] achieve intelligent recognition of axis orbit by combining Hu moment invariants and fractal box dimension.

However, due to the use of simple machine learning algorithms, the identification accuracy of the above methods for the axis orbit data under complex working conditions are relatively low, especially in the face of large sample data input. To solve this problem, this paper introduces the convolution neural networks (CNN) into the field of rotating machinery axis orbit identification, and proposes a rotating machinery axis orbit identification method based on CNN by using its high-dimensional complex feature recognition ability. By preprocessing the vibration signals of the shaft and constructing the CNN, different kinds of rotating machinery axis orbit can be identified automatically, and assist the expert system to realize real-time fault diagnosis. The main contributions of this paper are summarised as follows:

1) CNN is introduced to identify the axis orbit of rotating machinery using its dimensional complex feature recognition capability.
2) A axis orbit preprocessing method that includes multi level purification operation is proposed to transform axis signals into unified two dimensional matrix as CNN input.
3) The proposed method shows good universality and achieves accuracy over 73% in field data identification.

The rest of this paper is organized as follows: Section 2 presents the axis orbit shape under common faults. The proposed fault diagnosis method that combines vibration signals preprocessing and CNN is described in Section 3. Section 4 presents experimental verification based on experimental data and field data, which is followed by concluding remarks in Section 5.

2. Axis Orbit of Rotating Machinery
For the common faults of the shaft in rotating machinery, the unbalanced force generated by the fault will cause the position change of the shaft during rotation, resulting in the change of the shaft running track. The monitoring and judgment of the axis orbit can help to judge the fault type, especially in the analysis of rotor stability, balance, alignment, friction and other aspects [16].

The axis orbit has a good correspondence with the static load, rub impact and instability in the system. For a well running rotor in a system, the axis orbit should be a circle if the non-uniformity of its constraint stiffness is not considered. However, due to the uneven support stiffness of the system, it is generally an elliptical axis orbit, as shown in Figure 1. The ellipticity of the orbit reflects the degree of non-uniform stiffness of the support and the magnitude of the force, so it is easy to obtain the running state of the rotor in the bearing through the axis orbit.

![Figure 1. Normal axis orbit.](image_url)
When there are straight edge, reverse precession and disorder in the axis orbit, enough attention should be paid to the rotor. The change from ellipse to "banana" shape, and then to "8" shape, is a typical reflection of the load effect, as shown in Figure 2. The "plum shaped" shape is mostly related to instability. The more beautiful the axis orbit is, the more serious the instability will be. In addition, when the obvious "straight line" appears in the axis orbit, it is also one of the "evidences" of rubbing or friction.

Figure 2. The axis orbit with the increase of preload.

The inner ring in the axis orbit is formed because the whirling shape of the rotor is changed when the rotor rubs with the bearing bush. The more the inner rings are, the more serious the rub impact is, which indicates that there are more rubbing points in the bearing, as shown in Figure 3.

Figure 3. Slight rubbing, severe rubbing and severe friction.

From the above analysis, it can be seen that the axis orbit is very important to judge the fault of rotating machinery. However, in the field diagnosis, the shape of the axis orbit is various, which requires the operator to make manual judgment according to the professional knowledge. Then the expert system cannot realize the intelligent diagnosis without intelligent identification of axis orbit.

3. Intelligent Identification Method of Rotating Machinery Axis Orbit Based on CNN

Based on the analysis of the common axis orbit shape of rotating machinery, combined with the CNN successful applied in many fields, this paper proposes an intelligent recognition method of rotating machinery axis orbit based on CNN. The flow chart of the proposed method is as shown in Figure 4.

3.1. Vibration Signal Acquisition

The vibration displacement sensors are installed on the shaft to collect the vibration displacement signal of rotating machinery. In order to obtain the axis orbit, a pair of displacement sensors are installed with an included angle of 90 degrees. At the same time, the phase information is very important in the fault diagnosis of shaft, so the synchronous integrated period sampling is needed. In general, the sampling frequency of synchronous integrated period sampling is 2n times (n > 5) of the rotating speed of the rotating machinery, and the sampling length is 2k rotation cycles (k ≥ 3).

3.2. Axis Orbit Preprocessing

Since CNN is usually used to process two-dimensional or three-dimensional input, in the preprocessing stage, it is necessary to convert the vibration signals of the shaft into an appropriate image as CNN input. In the process of rotating machinery operation, the phase and amplitude of vibration signal will change due to the change of rotating speed, load and other operating conditions. In order to unify the axis trajectories at different speeds, a method proposes a method to extract the
axis orbit, which can transform the vibration signals into a matrix with the same format as CNN input. The steps are as follows:

1) Axis orbit purification

For the common faults of rotating machinery, the first and second order rotating frequency are the main vibration components, which basically reflect the running track of shaft. However, the vibration component above the second harmonic frequency, although the energy is small, will make the orbit of the axis orbit chaotic. Figure 5 shows the axis orbit during the start-up process when the misalignment fault occurs in the experiment. It can be seen that the axis orbit is chaotic and impossible to be identified directly. Therefore, the purification of the original axis orbit is necessary.

Figure 5. The original axis orbit with rotor misalignment fault.

In this method, frequency domain filtering is used to purify the axis orbit. Firstly, Fourier transform of X direction sensor signal \( x(t) \) and Y direction sensor signal \( y(t) \) is carried out to obtain the frequency domain complex sequence \( F_x \) and \( F_y \).

\[
F_x(\omega) = \int_{-\infty}^{+\infty} x(t)e^{-j\omega t} dt \\
F_y(\omega) = \int_{-\infty}^{+\infty} y(t)e^{-j\omega t} dt
\]  

(1)

Then, in the frequency domain, the value corresponding to the frequency component greater than 2 times frequency is set to 0, and the new sequences \( F_x' \) and \( F_y' \) are obtained.

\[
F_x'(\omega) = \begin{cases} 
F_x(\omega), & (\omega \leq 2f_r) \\
0, & (\omega > 2f_r)
\end{cases}
\]

\[
F_y'(\omega) = \begin{cases} 
F_y(\omega), & (\omega \leq 2f_r) \\
0, & (\omega > 2f_r)
\end{cases}
\]  

(2)

where \( f_r \) is the rotational frequency of the rotor. Furthermore, the filtered vibration signals \( x' \) and \( y' \) can be obtained by inverse Fourier transform of \( F_x' \) and \( F_y' \), and the purified axis orbit can be obtained by correlating \( x' \) and \( y' \).

\[
x'(t) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} F_x'(\omega)e^{j\omega t} d\omega \\
y'(t) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} F_y'(\omega)e^{j\omega t} d\omega
\]  

(3)
Figure 6 shows the purification result of the axis orbit with rotor misalignment fault in Figure 5. It can be seen that the axis orbit shape in the figure is an obvious ‘8’.

![Figure 6. Axis orbit after purification.](image)

After purification, it can still be seen that the axis orbit of different periods are still different at variable speed. In order to further eliminate the influence of variable speed, the axis orbit in each period is further averaged. The coordinates of the axis position on the same phase of each period and its adjacent periods are averaged to make the shape of the axis orbit more centralized.

\[
x''(2^n m + t) = \frac{1}{3} \sum_{j=m-1}^{m+1} x''(2^n j + t),
\]

\[
y''(2^n m + t) = \frac{1}{3} \sum_{j=m-1}^{m+1} y''(2^n j + t),
\]

\[1 \leq m \leq 2^k - 2, \quad 1 \leq t \leq 2^n\]

(4)

where \(x''\) and \(y''\) are the axis orbit after moving average. Figure 7 shows the average axis orbit obtained from the axis orbit in Figure 6 by sliding average. It can be seen that the shape of axis orbit is more prominent, which provides convenience for intelligent recognition of CNN.

![Figure 7. Moving average axis orbit.](image)

2) Matrix transformation of axis orbit
Since CNN can only process fixed input, it is necessary to transform the image of axis orbit under different operating conditions into a unified matrix. Therefore, this paper proposes an algorithm for transforming the vibration signal to the matrix of axis orbit.

Firstly, the maximum amplitude $V_{\text{max}}$ of vibration signal is obtained by:

$$V_{\text{max}} = \max \{ \max \{|x^a|\}, \max \{|y^a|\} \}$$  \hspace{1cm} (5)

Then, 1.2 times of $V_{\text{max}}$ is taken as the amplitude range of the matrix, and the corresponding amplitude range of each element of the matrix is further divided.

$$v_i = [(i - m/2) \times d, (i + 1 - m/2) \times d]$$

$$v_j = [(j - m/2) \times d, (j + 1 - m/2) \times d]$$

$$d = 2.4 \times V_{\text{max}} / m$$

where $v_i$ and $v_j$ are the horizontal and vertical amplitude ranges of the matrix at $(i, j)$, respectively; $d$ is the amplitude resolution of the matrix, and $m$ is the size of the axis orbit matrix.

Finally, the axis orbit matrix $P$ with all zeros is constructed, and the axis orbit is drawn in the matrix.

$$P_{i,j} = P_{i,j} + 1 \hspace{1cm} (x_k \in v_i, y_k \in v_j, k = 1, 2, \ldots, n)$$  \hspace{1cm} (7)

where $P_{i,j}$ are the values of the axis orbit matrix at $(i, j)$. For each point in the axis orbit, find its corresponding position in the axis orbit matrix, and increase the matrix value of the position by 1.

Figure 8 shows the matrix of the axis orbit in Figure 7. It can be seen that the axis orbit well shows the shape of the axis orbit and can be directly used as the input of CNN.

![Figure 8. Axis orbit matrix.](image)

### 3.3. CNN Construction and Training

CNN mainly consists of two basic layers: convolution layer and pooling layer. The input of each neuron in the convolution layer is connected with the local area of the feature map of the previous layer. The local features are extracted by convolutional kernel, and the relative position relationship of the features is preserved. The pooling layer can reduce the size of feature map and further extract features by finding the maximum or average value of feature map in a certain range [17].

Each convolution kernel of convolution layer performs convolution operation on the limited range across the input feature map. For each input feature map, the convolution layer has $k$ convolution kernels will obtain $k$ output maps. With a the input $X$ in a size of $M \times N$, the output of convolution layer can be calculated by:

$$h^k_{i,j} = \theta((W^k \ast X)_{i,j} + b_k)$$  \hspace{1cm} (8)
where $h_{i,j}^k$ is the value of the $k$-th feature map obtained by the $k$-th convolution kernel of the input feature map at coordinates $(i,j)$ ($i=1,2,\ldots,M-s+1$, $j=1,2,\ldots,N-s+1$). $W^k \in R^r$ is the weight of the $k$-th convolution kernel, $s$ is the size of the convolution kernel, $b_k$ is the offset of the $k$-th convolution kernel. $\theta(x)$ is the activation function, which is usually set as the ReLU function. The calculation formula of ReLU is as follows:

$$\text{ReLU}(x) = \begin{cases} 
    x, & x > 0 \\
    0, & x \leq 0
\end{cases}$$

The pooling layer samples the features of different positions on the input feature map to reduce the size of the feature map obtained by convolution layer. Common pooling operations include maximum pooling and average pooling. The calculation method of average pooling is as follows:

$$P_{i,j} = \frac{1}{s^2} \sum_{m,n=1}^{s} h_{(i-1)s+m,(j-1)s+n}$$

where $P_{i,j}$ is the value of the output image of the pooling layer at coordinates $(i,j)$, $s$ is the pooling size, and $h_{(i-1)s+m,(j-1)s+n}$ is the value of the input feature map at the coordinate $((i-1)s+m,(j-1)s+n)$.

CNN training is a supervised training process. Using back-propagation algorithm, the parameters of convolution layer and fully connected layer are optimized by gradient descent until the training samples reach convergence.

Figure 9 shows a basic CNN structure, which consists of convolution layers, pooling layers. Finally, the feature maps are transformed into a one-dimensional vector as the input of fully connected layer. The output is obtained by the softmax classifier.

In the proposed method, the axis orbit matrix is used as CNN input, and the output of CNN is the category of axis orbit. The structural parameters of CNN can be determined according to the size of axis orbit matrix and the number of axis orbit categories. During the network training, in order to increase the sample number and diversity of the axis orbit matrix, each axis orbit matrix is transposed, flipped left and right, and flipped up and down, which are used as CNN input together with the original axis orbit matrix. In this way, the training samples are 4 times of the original samples, which can improve the stability and accuracy of training.

4. Case Study

In order to verify the effectiveness of the proposed method, a fault experiment of rotating machinery is carried out in this section, and the proposed method is applied to identify the axis orbit.

Figure 10 shows the structure of the rotating machinery test-bed used in the experiment, which can simulate a variety of faults. In this experiment, normal state and three kinds of faults, including rotor
unbalance, misalignment and bearing house looseness, are simulated. The shape of axis orbit includes ellipse, banana type, 8-shape and internal 8-shape. In order to cover the full working speed, the data of start-up and stable operation stages are collected in each state. A pair of horizontal and vertical displacement sensors are used to monitor the vibration. The sampling frequency is 64 times of the rotating frequency, and each samples contains 8 rotation cycles.

![Figure 10. Structure of the test bed.](image)

In the experimental verification, 1032 samples are selected from the fault data, and each sample contains the data of horizontal and vertical sensors. The number of samples for each axis orbit is different. The number of ellipse, banana shaped, 8-shaped and inner-8-shaped are 356, 304, 184 and 188 respectively. The unbalanced samples are more in line with the field situation. In order to better verify the identification effect of the proposed method, 1032 samples are classified into four groups, labeled as A, B, C and D. In each training, three groups are selected as training set and the remaining group as test set.

When preprocessing the vibration data of the displacement signals, firstly, the vibration signals in X direction and Y direction are combined into the axis orbit. Then the axis orbit are purified and the moving average operation is carried out. Finally, the axis orbit is transformed into the matrix with a size of 100 × 100 as the input of CNN. The structure of CNN in the experiment are shown in Table 1, and the learning rate is set to 0.005.

| Layer | Type            | Kernel size | Kernel number | Output size  |
|-------|-----------------|-------------|---------------|--------------|
| 0     | Input           | -           | -             | 100×100×1    |
| 1     | Convolution layer | 5×5×1      | 50            | 96×96×50     |
| 2     | Max pooling layer | 2           | -             | 48×48×50     |
| 3     | Convolution layer | 5×5×50     | 50            | 44×44×50     |
| 4     | Max pooling layer | 2           | -             | 22×22×50     |
| 5     | Convolution layer | 5×5×50     | 100           | 18×18×100    |
| 6     | Max pooling layer | 2           | -             | 9×9×100      |
| 7     | Convolution layer | 4×4×100   | 100           | 6×6×100      |
| 8     | Max pooling layer | 2           | -             | 3×3×100      |
| 9     | Convolution layer | 3×3×100   | 200           | 1×1×200      |
| 10    | Fully connected layer | 1×1×200 | 4             | 4            |
| 11    | Classifier      | Softmax     | -             | 1            |

In the experiment, the training of CNN is based on MATLAB. The server configuration is two E5-2667v3 processors, a GTX1080ti GPU and 64GB memory. The training process is calculated by GPU, and the program of CNN is realized by MatConvnet toolbox[18].

In each combination of training data sets, after about 30 training steps, CNN achieves convergence. The loss curve of the combination using A, B and C as training set is shown in Figure 11, which shows that the training process is stable.
The identification accuracy of each combination of training datasets is shown in Table 2. Moreover, the results of the method proposed in this paper are compared with those using image invariant moments and PNN. It can be seen from the table that the method proposed has a high accuracy rate for the shape identification of axis orbit. Compared with the method in the literature, each combination has a higher accuracy, and the average accuracy is more than 10 percent higher. It is proved that the method based on CNN is an effective method to identify the axis orbit of rotating machinery.

**Table 2.** Comparison of different identification methods for axis orbit.

| Training / Test set | CNN     | invariant moments + PNN |
|---------------------|---------|-------------------------|
| A B C/D             | 86.82%  | 75.58%                  |
| A B D/C             | 86.43%  | 72.09%                  |
| A C D/B             | 85.27%  | 74.42%                  |
| B C D/A             | 86.63%  | 76.36%                  |
| Average             | 86.29%  | 74.61%                  |

In order to further verify the generality of the proposed method, the CNN model trained by experimental data is used to identify an actual steam turbine shaft orbit. The unit is a 1 × 300MW cogeneration steam turbine, and thermal bending occurs during operation. The data set includes 137 data samples for normal start-up, normal operation and fault shutdown. There are ellipse, banana shaped and 8-shaped axis orbit. Figure 12 shows the examples of each axis orbit shape in the data set.

**Figure 12.** Axis orbit of a steam turbine.

The identification results of the axis orbit are shown in Table 3. It can be seen that the accuracy rate of the model trained by the experimental data is more than 78% for the actual unit axis orbit identification, which shows the universality of the method.
Table 3. Identification results of actual turbine axis orbit.

| Axis orbit shape | Sample number | Correct number | Accuracy  |
|------------------|---------------|----------------|-----------|
| Ellipse          | 15            | 11             | 73.33%    |
| Banana shaped    | 45            | 39             | 86.67%    |
| 8-shaped         | 77            | 57             | 74.03%    |
| Total            | 137           | 107            | 78.10%    |

5. Conclusion
In this paper, a novel method based on CNN is proposed to identify the axis orbit shape of rotating machinery. The method makes full use of the powerful feature recognition ability of the CNN and combines with the axis orbit purification algorithm to realize the real-time intelligent identification of axis orbit. In the experiment of identifying the axis orbit of a variable speed turbine rotor test-bed, the identification accuracy is more than 85%, which shows the effectiveness of the method. The CNN model trained with experimental data also has a high accuracy rate for the identification of the actual turbine axis orbit, which further shows the universality of the method.

References
[1] Fan J, Xiao B, Gao S, et al. Real-time Online Diagnosis of Vibration Faults in Rotary Machineries. Dongli Gongcheng Xuebao/Journal of Chinese Society of Power Engineering, 2018, 38(2):120-126.
[2] Tian Y, Ma J, Lu C, et al. Rolling bearing fault diagnosis under variable conditions using LMD-SVD and extreme learning machine. Mechanism and Machine Theory, 2015, 90:175-186.
[3] Pan L, Zhu D, She S. Gear Fault Diagnosis Based on Multi-Dimensional Feature Representation and SVM. Machinery Design & Manufacture, 2019:104-107.
[4] Li Q, Hou R, Ding X. Roller bearing fault diagnosis based on improved stacked auto-encoder. Computer Engineering and Design, 2019, 40(07):2064-2070.
[5] Zhou Q, Liu X, Zhao J, et al. Fault diagnosis for rotating machinery based on 1D depth convolutional neural network. Journal of Vibration and Shock, 2018, 37(23):31-37.
[6] Sheng G, Tao Y, Wei G, et al. A Novel Fault Diagnosis Method for Rotating Machinery Based on a Convolutional Neural Network. Sensors, 2018, 18(5):1429-.
[7] An M. A Survey on Fault Diagnosis Expert Systems. Computer Measurement & Control, 2008, 16(9):1217-1219.
[8] Deng T, Hong Y. Diagnosis Method of Turbine Fault Diagnosis and Low Frequency Oscillation. Turbine Technology, 2015, 57(05):391-392+395.
[9] Li Y. Fault Diagnosis of Turbine Generator Sets Based on Ontology and Case Reasoning. Lanzhou University of Technology, 2019.
[10] Li Y. The Fault Diagnosis of Large-scale Wind Turbine Based on Expert System. Shenyang University of Technology, 2011.
[11] Xinyu P, Zhaojian Y, Jianxiang Y, et al. Recognition of torque load for elastic support rotor system based on axis orbit. 2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI). IEEE, 2016.
[12] Zheng C, Guangrui W, Zhifen Z, et al. Rotor Fault Degree Identification and Indication with Information Entropy and Box Counting Dimension of Axis Orbit[J]. Journal of Xi'an Jiaotong University, 2019.
[13] Xu J. Research on Purification, Feature Extraction and Automatic Identification of Rotor Axis Orbit. North China Electric Power University, 2017.
[14] Yuan X, Liu D, Hu X, et al. Research on the Feature Extraction of Hydropower Units Shaft Orbit Based on Improved Moment Invariants and PNN. China Rural Water and Hydropower, 2019,(06):149-152+158.
[15] Jie S, Xinyu P, Zhaojian Y, et al. Research on intelligent recognition of axis orbit based on Hu moment invariants and fractal box dimension. 2017 14th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI). 2017.

[16] Xiang L, Zhang Y. Fault Analysis of a Cracked Rotor Based on Morphological Characteristics of Axis Orbits. Dongli Gongcheng Xuebao/Journal of Chinese Society of Power Engineering, 2018, 38(5):380-385+399.

[17] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature, 2015, 521(7553): 436-444.

[18] A. Vedaldi and K. Lenc, Matconvnet: Convolutional neural networks for matlab. Proceedings of the 23rd ACM International Conference on Multimedia, 2015:689–692.