Convolution Diagnosis Model of Centrifugal Pump Based on Fractal Dimension

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Abstract. Nowadays, more and more centrifugal pumps are used in the industrial domain. Normal operation of centrifugal pumps is also the key to maintain stable operation of production and process. So it is very important to monitor the operation status of centrifugal pumps real time on-line. In order to diagnose the fault of centrifugal pumps, we proposed a Convolutional Neural Network (CNN) fault diagnosis model, based on Fractal Dimension (FD) features. Firstly, we collected the vibration signal of centrifugal pumps and preprocessed them. Then we used the Empirical Mode Decomposition (EMD) to calculate the fractal dimension and the fractal matrix of the signal. Finally, we constructed the CNN model to diagnose and classify the fault of centrifugal pumps. The experiment shows that the accuracy of the proposed model can reach over 90%.

Keywords: Fractal dimension; Convolutional neural network; Centrifugal pumps diagnose.

1. Introduction

Nowadays, with the rapid development of industry and the further expansion of production scale, industrial production is highly integrated. Once problems occur in the production system, it will produce a chain reaction, which leads to serious security risks, production accidents, and heavy economic loss. Therefore, accurate fault diagnosis of equipment for timely predictive maintenance is of great significance to reduce production risks and improve the safety of industrial activities.

As a research hot spot in industry domain, the fault diagnosis of equipment has been widely studied by many researchers. Fault diagnosis of centrifugal pumps is one of the most important research fields. Among researchers, Shengguo Zhang et al. analyzed the causes and influencing factors of centrifugal pump vibration[1]. Yunlong Zhou et al. used pressure pulsation to diagnose cavitation fault of variable speed centrifugal pump[2]. Yongxing Song used principal component analysis and cyclostationary analysis to extract the acoustic characteristics of centrifugal pump and analyzed the fault[3], this method have good diagnosis effect on common centrifugal pump faults. Qichao Liu et al. proposed a fault diagnosis method for centrifugal pump based on complexity characteristics and fault characters analysis of empirical mode decomposition[4]. Soylemezoglu A et al. proposed Mahalanobis Taguchi system to extract and analyzed features of centrifugal pumps, and diagnosed faults of mechanical seal,
impeller, filter and other parts of centrifugal pumps. Wang H et al. used mean, variance, kurtosis, skewness and other statistical parameters as fault features, combined with fuzzy neural network to diagnose cavitation, rings wearing, rotor imbalance and other faults of centrifugal pump. Sakthivel N R et al. used Decision Tree and rough set in fault diagnosis of centrifugal pump, and carried out comparative verification. Stopa M et al. used the load torque signal to do spectrum analysis to diagnose the cavitation fault of centrifugal pump, and achieved good results.

As an important research method in modern data science and nonlinear mathematics, fractal theory plays an important role in data analysis and process in various domain. Fractal theory describes the similarity of whole and parts, which can be used to quantitatively describe the fractal characteristics of nonlinear system and determine the filling relationship between signal and space. In the fault diagnosis of equipment, different faults have different nonlinear influence factors, and the FD can extract the fault characteristics of equipment, so as to classify and identify different faults. For example, based on fractal theory, Yuxiu Xu established a sample space library with signal FD as feature group, proving that fractal theory can analyze and process fault diagnosis and classification of equipment.

In recent years, deep learning algorithm based on big data has been widely used in text recognition, target detection and other fields, also achieved good results. Therefore, on the basis of the traditional EMD processing method, this paper introduced CNN and combined it with FD to form a fault diagnosis model of centrifugal pump to diagnose and classified the fault of centrifugal pump. The following are the main contributions of this article:

1. Extract the fractal feature matrix from the collected signals;
2. Propose artificial simulation method for pump fault base on the diagnosis experience;
3. Build CNN model to diagnose and classified the fault of centrifugal pump, the accuracy can reach above 90%.

2. Characters of Fractal Dimension

2.1. EMD

EMD can be used to decompose most nonlinear and nonstationary signals. It has great advantages, which is widely used in industry field. The main idea is to decompose the complex original signal into multiple Intrinsic Mode Functions (IMF). That is, decompose multiple single frequent waves and residual waves. There are two preconditions for EMD process: First of all the number of data extremum is not less than two. Meanwhile the local time-domain characteristics of the data are uniquely determined by the time scale of the extremum. If the data only has inflection point but no extremum point, it is necessary to differentiate the data for extremum, and then integrate to get the result. Multiple IMF components obtained by EMD decomposition can represent the signal characteristics in different time scales. The specific steps of EMD method are as follows: find the extreme point of the original signal \( s_t \), use cubic spline interpolation method to form the upper envelope of the maximum fitting curve \( U_t \), form the lower envelope of the minimum fitting curve \( L_t \), and calculate the mean value to get the average envelope.

\[
m_t(t) = \frac{U_t + L_t}{2}
\]

\( s_t \) subtract \( m_t(t) \), then we can get a new sequence \( h_t(t) \)

\[
h_t(t) = s_t - m_t(t)
\]

After that, we can judge whether \( h_t(t) \) is IMF by:

I The number of zeros and extremum points of the signal is equal or differ one;
II The mean values of maximum envelope and minimum envelope are equal to 0.
If \( h(t) \) does not satisfy the above conditions, then let \( s_i \) replace \( h(t) \), repeat the above steps, get a new sequence \( h_1(t) \):
\[
h_1(t) = h(t) - m_1(t)
\]
(3)

According to the above IMF criterions, we can get \( \text{imf}_i(t) \) until \( h_m(t) \) satisfy the conditions of IMF for the first time, \( s_i \) subtract \( \text{imf}_i(t) \), the residual signal is obtained:
\[
r(t) = s_i - \text{imf}_i(t)
\]
(4)

Then let \( r_1(t) \) replace \( S_i \), repeat the above steps, we can get multiple IMF components and the last non-separable residual sequence, record it as trend term \( r_n(t) \), the EMD algorithm expression can be recorded as:
\[
s_i = \sum_{i=1}^{n} \text{imf}_i(t) + r_n(t)
\]
(5)

In this paper, EMD is used to decompose the original signal waveform, and the first five IMFs components IMF1-IMF5 are selected to calculate their fractal dimension.

2.2. FD

FD is a parameter that can be used to measure the fractal characteristics of data, and it is a measurement parameter formed by quantized fractal characteristics\(^{[11]}\), so the form of fractal dimension is simple and intuitive. In this paper, the change of fractal dimension is recorded to distinguish the different states of signal, so as to recognize the fault signals of equipment.

The CNN diagnosis model based on FD represents the running state of centrifugal pump with fractal dimension, and carries out training analysis with it. When using fractal dimension to represent the state, a straight line can be used to represent the state space of the device, and different line segments can be used to distinguish different states, as shown in Figure 1.

![Figure 1. Partition of Equipment State Space by Fractal Dimension.](image)

Assuming that the equipment has \( N \) different states, \( N \) different intervals can be divided in the line segment of the equipment state space. The minimum and maximum of the fractal dimension of the state are the minimum and maximum of the interval respectively. For example, state 3 in Figure 1, it’s state interval is \( [D3, D3'] \), \( D3 \) and \( D3' \) represents the value of fractal dimension at the end of state 3.

Let the state space of the device be \( S \), the \( j \) th state interval of the device be \( S^j \), then
\[
S^j = [Dj, Dj']
\]
(6)

Among them, \( j = 1, 2, 3 \cdots N \), \( Dj \) and \( Dj' \) is the minimum and maximum of the fractal dimension in this state, so the interval of the state \( j \) can be obtained
\[
|S^j| = [Dj, Dj']
\]
(7)
The length of different state intervals is determined by the maximum and minimum of the fractal dimension of the interval. The state space is a straight line and the equipment state is a line segment. Therefore, the useful state region \( S^u \) in the state space is as follows:

\[
S^u = S^1 \cup S^2 \cup \cdots \cup S^N
\]  

(8)

And the useless state region where don’t have corresponding state is

\[
\bar{S}^u = S - S^u
\]  

(9)

Therefore, the partition of state space is very important for using fractal dimension as the criterion of state differentiation, which can clearly divide different state spaces and is also conducive to fault diagnosis. For the partition of state space, the following conditions should be satisfied:

\[
\begin{cases}
S^1 \neq 0 \\
S^1 \cap S^2 \cap \cdots \cap S^N = 0
\end{cases}
\]  

(10)

It can be seen from (10) that the interval set of each state should not be empty and there is no intersection between them. In practice, the fractal dimension range of different states of equipment has a certain fluctuation range, which will produce intersection, so it is difficult to judge its state. In addition, if there are two or more kinds of state features in the signal, it is impossible to determine the state if they overlap each other. Therefore, this paper uses the detrend dimension, box dimension, petrosian dimension and higuchi dimension to represent the equipment state, and increases the state interval.

In this way, the original signal is decomposed with EMD to get five IMFs, and then the fractal characteristics are calculated based on the above four dimensions to get the twenty dimensional fractal characteristic matrix of the original signal. With the state characteristics of the equipment, CNN can be used for training analysis and fault diagnosis.

3. Fault Diagnosis by Convolutional Neural Network

3.1. CNN

After EMD decomposition of the original signal and the characteristic matrix obtained by calculating the FD, the CNN can be used to train and classify the state matrix. The operation process of the CNN is as follows:

\[
Y = H(X, W) = f \left( \cdots f \left(X \otimes W^{(1)} \otimes W^{(2)} \cdots \right) \right)
\]  

(11)

Where \( X \) is the input of the neural network, namely the characteristic matrix. \( Y \) is the output of neural network, namely fault classification; \( H(\bullet) \) represents the nonlinear mapping function of the CNN, namely the activation function; \( W^{(l)} \) represents the weight parameter of the \( l \)th convolutional layer, and the operation is updated by the back propagation algorithm.

The training process of CNN model includes the following steps:

Step1: Initialize the weight parameter \( W \) of the CNN².

Step2: Forward propagation calculation. Input the training data into the CNN and use the forward propagation formula to calculate the activation parameters of each layer of the network.

Step3: Calculate the loss function of the output layer.

Step4: Calculate the error term \( \delta^{(l)} \) of all convolutional layers according to the error back propagation algorithm and chain derivation rule.
\[
\delta_j^{(l)} = \frac{\partial J}{\partial Z_j^{(l)}} \\
= \left( \sum_{j=1}^{M} \delta_j^{(l+1)} * W_{ij}^{(l+1)} \right) \otimes f'(Z_i^{(l)})
\]

Where \( M \) is the number of the \( l+1 \) layer characteristics graph, \( \delta_j^{(l+1)} \) expression a figure characteristics of the error term of the \( l+1 \) layer’s the \( j \) th feature map, \( W_{ij}^{(l+1)} \) represents weights between the \( l+1 \) layer of the \( j \) th convolution response characteristics map and the output characteristics of the map \( i \) in \( l \) layer, \( Z_j^{(l)} \) is the convolution response character map for the \( j \) map of the layer the \( l \), \( f'(Z_i^{(l)}) \) is the derivative for the layer activation function, "*" represents convolution operation.

Step 5: Calculate the weight gradients of all convolutional layers.
Step 6: Update weight parameters:

\[
V(t+1) = \mu V(t) - \eta \left[ \frac{\partial J}{\partial W(t)} + \lambda W(t) \right]
\]

\[
W(t+1) = W(t) + V(t+1)
\]

Where \( t \) denotes the number of iterations, \( V(t) \) denotes the momentum, \( \mu \) denotes the momentum factor, \( \eta \) denotes the learning rate, and \( \lambda \) denotes the weight attenuation coefficient.

Step 7: Repeat step 2 to step 6 until convergent.

3.2. Network Structure
In this paper, we mainly used the four fractal dimensions mentioned in section 2.2 to analysis fault, calculated the fractal dimension characteristic matrix as the data set of CNN, and divided it into training set and tested set according to the ratio of 9:1, used CNN for training and testing, and finally got the fault diagnosis results. The following is a brief introduction of CNN structure.

In this experiment, a convolution layer, two fully connected layers and a softmax layer were used to form the neural network. The iteration period was 3000, the number of batches was 512, and the learning rate was 0.0001. The convolution layer contained 20 convolution kernels, the size of kernels was \( 5 \times 5 \), and the activation function was ReLU(Rectified Linear Unit). Each layer contained 18 neurons. Finally, the softmax classifier was used to classify and diagnose the pump faults.

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**Figure 2.** Fault Diagnosis Flowchart.
4. Case Study

4.1. Experiment Setup
In this project, EMC-250MC-C37 vertical marine centrifugal pump was used to build a centrifugal pump test-bed, which was mainly composed of centrifugal pump, motor, connecting frame and coupling, the parameters of experimental centrifugal pump was shown in Table 1. The test pipeline was composed of water tank, inlet and outlet pressure measuring pipe, elbow, valve, measuring element, etc, as shown in Figure 3.

The signal collecting device consisted of eight vibration acceleration sensors as shown in Figure 3, each vibration signal was collecting for 30 minutes with a sampling frequency of 20 kHz, the signal and spectrum collected by sensors was shown in Figure 4 and Figure 5.

### Table 1. Parameters of experimental centrifugal pump.

| Parameters Name       | Value |
|-----------------------|-------|
| Flow (m³/h)           | 320   |
| Lift (m)              | 25    |
| Rotation Rate (r/min) | 1780  |
| Rated Power (kW)      | 30    |
| Necessary NPSH (m)    | 5     |
4.2. Experiment of Centrifugal Pump
In this experiment, sixteen centrifugal pump faults were simulated, including a control group and an experimental group, the fault simulation experiment of centrifugal pump was mainly realized artificially. The details of simulation were described in Table 2. The arrangement of sensors in the experiment is shown in Table 3.

5. Results

5.1. Result of Fractal Dimension
The diagnostic method based on the similarity of fractal matrix mainly consist of two parts: constructing the fractal matrix, and similarity analysis by Pearson distance.

The fractal matrix were constructed based on the first five IMFs through EMD, fractal dimensions(box dimension, higuchi dimension, detrend dimension and petrosian dimension) of each IMF were calculated, therefore obtained the twenty fractal dimensions of the signal as the fractal matrix.

Each thirty-minute signal detected by sensor 1 to 8 under different faults was seperated into frames of 1 second with length of 20k, the mean vector of frames under different conditions was chosen as the standard vector for similarity diagnosis.

The fractal matrix of each frame was compared with the standard vectors representing different faults, from which the closest one was taken as the final result, the similarities were obtained based on the pearson distance and the equition is shown as follow:
### Table 2. Fault List of Simulated Centrifugal Pump.

| Experimental Grouping | Fault Description of Experiment |
|-----------------------|---------------------------------|
| **Control Group**     |                                 |
| Full Performance       | From the zero flow condition, gradually increased to 120 percent of the rated flow |
| Rated Operation        | Two hours continuous operation under rated flow condition |
| **Fault Group**        |                                 |
| Slow Revolution        | Speed was adjusted to 1000 rpm |
| Foot Margin Loose      | Removed the two retaining bolts at the pump set outlet |
| Inlet Blocked          | Centrifugal pump inlet valve opened less than one third |
| Pump Reversal          | Reversed connection of two joints in the three-phase circuit, so that the centrifugal pump reverse |
| O-ring Teared          | Artificial teared O-ring of centrifugal pump |
| Machine Sealing        | Rub the mechanical seal between the stationary and rotating rings with grit |
| The Dynamic and Static Rings were Damaged | After artificial destruction of the dynamic and static ring, and then put into the pump |
| Angle of Installation  | Increased bevel metal pad between mechanical seal gland and pump cover |
| Pump Blocked           | Add wood block to seal the blade passage |
| Rotor Imbalance        | Add counterweight at the rear cover of impeller |
| Wear of Sealing Ring   | Process the inner diameter of the sealing ring mounted on the pump body and pump cover to 125mm |
| Inlet Pipe Intake      | Pump normal operation, loosen the bolts on the inlet flange after the pump |
| Misalignment           | Add 2-5 sheets of paper pad on one side between the rigid coupling and the large plate of pump shaft |
| Pump Friction          | Replace the seal ring on the pump with an eccentric seal ring |
| Cavitation             | Close the inlet valve and adjust the outlet valve |
| Pump Heating           | Pump group running normally, close the outlet valve |
Table 3. Sensor Distribution Scheme.

| Sensor Serial Number | Sensor Location       | Sampling Rate (kHz) | Sampling Duration (min) |
|----------------------|-----------------------|---------------------|-------------------------|
| 1                    | Motor Cover           | 20                  | 30                      |
| 2                    | Motor Housing         | 20                  | 30                      |
| 3                    | Flange Left           | 20                  | 30                      |
| 4                    | Flange Right          | 20                  | 30                      |
| 5                    | Bottom Left of Base   | 20                  | 30                      |
| 6                    | Bottom Right of Base  | 20                  | 30                      |
| 7                    | Upper Right Base      | 20                  | 30                      |
| 8                    | Upper Left Base       | 20                  | 30                      |

\[ p_{xy} = \frac{\text{cov}(X,Y)}{\sqrt{DX} \sqrt{DY}} \]  

The result of similarity diagnosis was shown in table 4, the accuracy of more than 90% was acquired under slow-revolution and inlet pipe intake, and 80% under the dynamic and static rings were damaged. It’s shown that the result isn’t satisfying under other conditions, their comprehensive index is lower than 80%.

5.2. Result of Neural Network

By calculating the characteristic matrix of fractal dimension, the similarity diagnosis of each fault was carried out, and the similarity judgment standard was constructed by taking the mean value according to the point, and the Pearson distance was selected as the similarity judgment basis, so the diagnosis effect was not ideal. This is because there is a phase difference between the sub frame signals, resulting in the method of taking the mean by point can not fully reflect the periodic components of the original signal.

Since the similarity diagnosis based on fractal dimension characteristic matrix can’t acquire ideal result, a CNN model based on fractal matrix was introduced in this paragraph. The fractal matrix of each frame was selected as the input feature, the training target was set as the one-hot code representing different faults. Six optimizers were adopted, including SGD, Adadelta, Ftrl, RMS, Adam and Nadam. The accuracy and loss curves during the training process were shown in Fig.6, where loss stood for the error between prediction and label, and accuracy stood for the performance of the CNN model. It is illustrated in Figure 6 that the accuracy and speed of convergence are relatively low when SGD, Adadelta, Ftrl are used as the optimizer comparing to RMS, Adam, Nadam, which have shown better performance with higher speed of convergence, losses stabilizing at 0.26 and accuracy at 90%.
Table 4. The Experiment Results of Fractal Dimension Similarity.

| Fault                        | Accuracy (%) | Recall (%) | False Positive Rate (%) | Underreporting Rate (%) | Comprehensive Index (%) |
|------------------------------|--------------|------------|--------------------------|-------------------------|-------------------------|
| O-ring Teared                | 79.0         | 78.8       | 1.10                     | 21.20                   | 78.90                   |
| Foot Margin Loose           | 37.50        | 47.90      | 2.90                     | 52.10                   | 42.10                   |
| Angle of Installation       | 58.00        | 43.40      | 2.20                     | 56.60                   | 49.60                   |
| Pump Reversal                | 59.10        | 46.20      | 1.70                     | 53.80                   | 51.90                   |
| Pump Blocked                 | 32.80        | 44.50      | 4.00                     | 55.50                   | 37.80                   |
| Pump Friction                | 61.50        | 61.30      | 2.00                     | 38.70                   | 61.40                   |
| Misalignment                 | 72.80        | 55.20      | 3.10                     | 44.80                   | 62.80                   |
| Slow-Revolution              | 99.40        | 88.30      | 0.10                     | 11.70                   | 93.50                   |
| The Dynamic and Static Rings were Damaged | 78.40 | 84.90 | 1.20 | 15.10 | 81.50 |
| Wear of Sealing Ring         | 44.30        | 52.70      | 3.30                     | 47.30                   | 48.10                   |
| Rotor Imbalance              | 44.80        | 16.40      | 1.40                     | 83.60                   | 24.00                   |
| Machine Sealing Damaged     | 50.60        | 80.40      | 3.30                     | 19.60                   | 62.10                   |
| Inlet Blocked                | 21.40        | 40.20      | 5.40                     | 59.80                   | 27.90                   |
| Inlet Pipe Intake            | 90.60        | 97.50      | 0.50                     | 2.50                    | 93.90                   |
| Cavitation                   | 30.80        | 51.10      | 4.20                     | 48.90                   | 38.40                   |
| Slight Pump Heating          | 62.40        | 64.70      | 2.10                     | 35.30                   | 63.50                   |

Figure 6. The comparison of loss and accuracy of different optimization algorithm.
Table 5 lists the fault diagnosis results of neural network training. It can be seen from the table that the diagnostic accuracy of O-ring teared, pump reversal, pump friction, misalignment, slow revolution, the dynamic and static rings were damaged, rotor imbalance, inlet pipe intake, cavitation is higher than 90%. The diagnostic accuracy of angle of installation, wear of sealing ring, machine sealing damaged, slight pump heating is higher than 80%. The diagnostic effect is better than similarity calculation, which proves that the CNN can distinguish all kinds of faults better.

| Fault                                      | Accuracy(%) | Recall (%) | False Positive Rate (%) | Underreporting Rate (%) | Comprehensive Index (%) |
|--------------------------------------------|-------------|------------|-------------------------|-------------------------|-------------------------|
| O-ring Teared                              | 90.00       | 96.40      | 0.20                    | 10.00                   | 93.10                   |
| Pump Heating                               | 64.60       | 73.50      | 0.80                    | 35.40                   | 68.80                   |
| Foot Margin Loose                          | 74.60       | 78.80      | 0.70                    | 25.40                   | 76.60                   |
| Angle of Installation                      | 85.20       | 89.00      | 0.70                    | 14.80                   | 87.10                   |
| Pump Reversal                              | 96.50       | 94.70      | 0.30                    | 3.50                    | 95.60                   |
| Pump Blocked                               | 58.10       | 85.30      | 0.40                    | 41.90                   | 69.10                   |
| Pump Friction                              | 92.70       | 92.50      | 0.40                    | 7.30                    | 92.60                   |
| Misalignment                               | 92.20       | 97.10      | 0.40                    | 7.80                    | 94.60                   |
| Slow-Revolution                            | 99.80       | 99.90      | 0.00                    | 0.20                    | 99.80                   |
| The Dynamic and Static Rings were Damaged  | 98.80       | 96.10      | 0.20                    | 1.20                    | 97.40                   |
| Wear of Sealing Ring                       | 89.00       | 73.70      | 1.60                    | 11.00                   | 80.60                   |
| Rotor Imbalance                            | 92.80       | 80.70      | 1.60                    | 7.20                    | 86.30                   |
| Machine Sealing Damaged                    | 86.90       | 92.50      | 0.30                    | 13.10                   | 89.60                   |
| Inlet Blocked                              | 76.40       | 71.00      | 1.10                    | 23.60                   | 73.60                   |
| Inlet Pipe Intake                          | 97.70       | 100        | 0.00                    | 0.23                    | 98.80                   |
| Cavitation                                 | 95.20       | 88.60      | 0.40                    | 4.80                    | 91.80                   |
| Slight Pump Heating                        | 87.50       | 75.10      | 1.50                    | 12.50                   | 80.80                   |

5.3. Discussion
According to the fractal dimension diagnosis results and neural network diagnosis results, the accuracy of using fractal dimension only to diagnose each fault of water pump is low, and only good results are obtained in the fault diagnosis of slow revolution, the dynamic and static rings were damaged and inlet pipe intake. However, the fault diagnosis using CNN neural network model has high accuracy in more than 80% of the faults, the overall accuracy can reach more than 90%. Therefore, the fractal dimension proposed in this paper can well characterize the fault of centrifugal pump. Through designed artificial simulation experiments and did experiments, it is verified that the fault diagnosis model based on
convolutional neural network proposed in this paper can achieve high accuracy in the fault diagnosis of centrifugal pump, and it’s an effective and feasible fault diagnosis method of centrifugal pump.

6. Conclusion
In this paper, a CNN diagnosis model of centrifugal pump based on fractal dimension was proposed. Firstly, the input signal was decomposed with EMD, then the fractal dimension of EMD component was calculated to form a fractal matrix. Finally, the CNN was used to train and classified the fractal matrix, and the fault diagnosis results were obtained. The experimental results show that the accuracy of the CNN diagnosis model can reach 90%. So that the diagnosis model can effectively monitor the state of centrifugal pump in real time, find the fault of centrifugal pump in time, and avoid greater losses.

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