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Rolling bearing fault diagnosis based on Minkowski similarity and GNN

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Abstract

Fault diagnosis is important for avoiding catastrophic accidents and ensure the safe operation of machinery, and a new fault detection method based on Minkowski similarity and Graph Neural Networks (GNN) is proposed in this paper. Firstly, the vibration signal as Euclidean structured data is converted into a Minkowski distance similarity matrix. Secondly, the dataset is fed into the GNN along with its corresponding labels, which contains the graph in each hidden layer of the network, enabling the graph neural network to learn the eigenvalues of itself and its neighbors. Finally, the first n objects that are difficult to reconstruct in the GNN output layer are determined to be faulty objects. The effectiveness of the proposed method in this paper is verified by using the public bearing dataset of Xichu University and Xi'an Jiaotong University. Experimental results show that the proposed method can accurately diagnose bearing faults.

Keywords

Graph Neural Networks; Minkowski similarity; Fault diagnosis

1. Introduction

Graph neural networks, also known as geometric deep learning, are based on graph representation learning [1], which obtains dependencies in the graph through the transfer of information between nodes in the graph, and can update the state of the node from neighbors at any depth of the node [2], which can represent label information. Since 2015, GNN has attracted a lot of attention, and it has been widely studied and applied in various fields such as node classification and recommender systems [3].

Based on traditional deep learning algorithms, graph neural network realizes the expansion of deep learning in the graph domain with the help of graph theory, semi-supervised learning and manifold learning theory and technology, and becomes a deep learning model with strong generalization ability and good stability. Compared with traditional deep learning methods, GNN can use the geometric structure relationship between data samples to make up for the shortcomings of insufficient category label information, and extract the local and global manifold structure features of the samples to improve the generalization performance of the model.

More and more scholars in the field of fault diagnosis have noticed the great potential of graph neural networks, and have gradually tried to apply them to the fault diagnosis of rolling bearings. Zhang et al. [4] established a Deep Graph Convolutional Network (DGCN) model consisting of a graph convolutional layer, a graph coarsening layer, and a graph pooling layer, and input the acoustic emission signal of the rolling bearing into the DGCN for fault diagnosis, which showed extremely high classification accuracy. Chen et al. [5] synthesized the observation data and prior knowledge, first used the structural analysis method to pre-diagnose the system fault, established the required correlation graph, then introduced the weight coefficient into the model to construct the GCN, adjusted the data influence weight, and finally used the improved GCN to realize the fault diagnosis of the rolling bearing. Li et al. [6] proposed a new Multi-Receptive Field Graph Convolutional Network (MRF-GCN) to obtain robust node features and designed a multi-receptive field graph convolutional layer.

In this paper, the Minkowski similarity model is used to create a feature map model, combined with GNN for bearing fault diagnosis, which overcomes the shortcomings of classical deep learning methods, GNN can make full use of the connection between the samples, and improve the generalization and stability of the diagnostic system, which brings a new concept to the fault diagnosis research of rolling bearings. Therefore, the fault diagnosis method of rolling bearings based on graph neural network is the focus of this paper.

2. Minkowski similarity principle

The Minkowski distance is a measure of space. The Minkowski distance between two n dimensional variables $x(x_1, x_2, \cdots, x_n)$ and $y(y_1, y_2, \cdots, y_n)$ is defined as

$$\mathrm{dist}(x, y) = \left(\frac{1}{n}\sum_{i=1}^{n}\left|x_i - y_i\right|^{P}\right)^{\frac{1}{P}} \tag{1}$$

where P can be a positive integer, $\mathrm{dist}(x, y) \in [0, \infty)$. The degree of match can be expressed as

$$\gamma(x, y) = \frac{1}{1 + \mathrm{dist}(x, y)} \tag{2}$$

where $1 + \mathrm{dist}(x, y) \in [1, \infty), \gamma(x, y) \in (0, 1]$.

The transient waveform sequence of household load can be regarded as n-dimensional vectors, and the degree of difference or matching between waveforms can be measured by the Minkowski distance. From the above, it can be seen that when $\mathrm{dist}(x, y)$ is closer to 0 and $\gamma(x, y)$ is closer to 1, it means that the difference between the two waveforms is smaller and the matching degree is greater. Conversely, the greater the difference, the smaller the match.

3. GNN principle

GNNs are a class of deep learning models for processing graph data [60]. Unlike traditional deep learning models, which can only process data with simple structures, such as tables or vectors, graph neural networks can directly process graph data, which has been widely used in images, natural language processing, social networks, and other fields. Based on the representation of the graph structure, the graph neural network takes nodes and edges as input data, learns the relationship between nodes and edges, and extracts features in the graph. Similar to traditional convolutional neural networks (CNNs), graph neural networks learn local and global features through a hierarchical structure. In each layer, the graph neural network updates the eigenvectors of each node and aggregates them with information from neighboring nodes for a higher-level representation. This aggregation operation can be implemented in a variety of ways, such as messaging, graph convolution, and so on. The main advantage of graph neural networks is their ability to directly process graph data, so they can handle a variety of complex relationships, such as dependencies between nodes, similarity between nodes, etc. In addition, graph neural networks can automatically discover relationships between nodes through end-to-end learning, thus avoiding the tedious process of manually designing features, as shown in Figure 1.

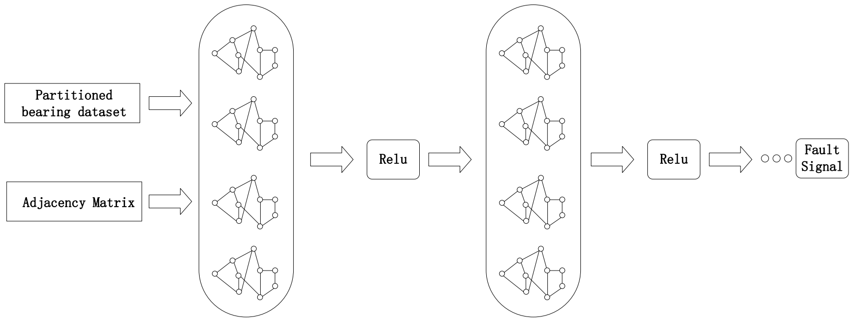

Figure 1. Envelope spectrum of the denoised signal

In a Euclidean structure dataset, objects are independent of each other and have no connection relationships. In this paper, we propose a graph construction method that uses M distance to transform the original disconnected relationship into a connected relation.

4. Bearing feature construction

The samples in the indicator set (also known as feature set) dataset are obtained by computing 17 metrics in the time and frequency domains, which are then used as inputs to the GNN model for fault detection to obtain the final detection results, as shown in Table 1.

Table 1. Characteristic indicators and calculation formulas

Indexes	Formula
Standard deviation	$I_1 = \sqrt{\sum_{n=1}^{N}(x(n)-\bar{x})^2 / N}$
Peak factor	$I_2 = \frac{\max\lvert x(t)\rvert}{\sqrt{\frac{1}{T}\int_0^T x^2(t)dt}}$
Skewness	$I_3 = S = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^3}{(\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2)^{\frac{3}{2}}}$
Kurtosis	$I_4 = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^4}{(\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2)^2}$
Root mean square	$I_5 = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Peak-to-peak value	$I_6 = \max x(t) - \min x(t)$
Variance	$I_7 = \frac{\sum_{n=1}^{N}(x(n)-\bar{x})^2}{N}$
Shape factor	$I_8 = \frac{\sqrt{T\int_{t_0}^{t_0+T}\left[f(t)\right]^2 dt}}{\int_{t_0}^{t_0+T}\left[x(t)\right]dt}$
Impulse factor	$I_9 = \frac{\max(x_n)}{\bar{x}}$

Fuzzy entropy	$I_{10} = -\sum_i q_i \cdot \log_e q_i$
Sample entropy	$I_{11} = -\ln(\frac{B^m(r)}{A^m(r)})$
Arrangement entropy	$I_{12} = -\sum_{i-1}^{N!} p(i)\log p(i)$
Approximate entropy	$I_{13} = \Phi^m(r) - \Phi^{m+1}(r)$
Center of gravity frequency	$I_{14} = \frac{\int_{-\infty}^{\infty} f \cdot I_{17}(f)df}{\int_{-\infty}^{\infty} I_{17}(f)df}$
Mean square frequency	$I_{15} = \frac{\int_{-\infty}^{\infty} f^2 \cdot I_{17}(f)df}{\int_{-\infty}^{\infty} I_{17}(f)df}$
Frequency variance	$I_{16} = I_{15} - \left(I_{14}\right)^2$
Power spectral density	$I_{17} = \lim_{T\to\infty} \frac{1}{T}\left\|X_T(f)\right\|^2$

where N is the number of the data points； *x(n)* and *x* denote the data sequence and mean of the data sequence, respectively; q_i indicates the likelihood or membership of the i fuzzy set element; B^m represents the number of subseries pairs of length m in a time series with similarity less than or equal to r; A^m represents the number of subseries pairs of length $m+1$ in a time series with similarity less than or equal to r; r is the similarity threshold, which is used to determine whether two subsequences are similar; $N!$ is the number of all possible permutations, where N is the number of different elements in the time series; $p(i)$ is the probability of the occurrence of the *i-th* permutation.

5. Experimental verification

5.1. Bearing dataset of Western Reserve University

The whole platform consists of a 2 horsepower motor [7], power tester and torque sensor as shown in Figure 2. The dataset is mainly divided into driver acceleration data, fan acceleration data, basic acceleration data, time series data and RPM, with sampling frequencies of 12 kHz and 48 kHz. This time, the base acceleration data with a sampling frequency of 12 kHz are selected, including the inner ring fault, the outer ring fault and the rolling element fault with a fault diameter of 0.1778 mm. The specific types are shown in Table 2.

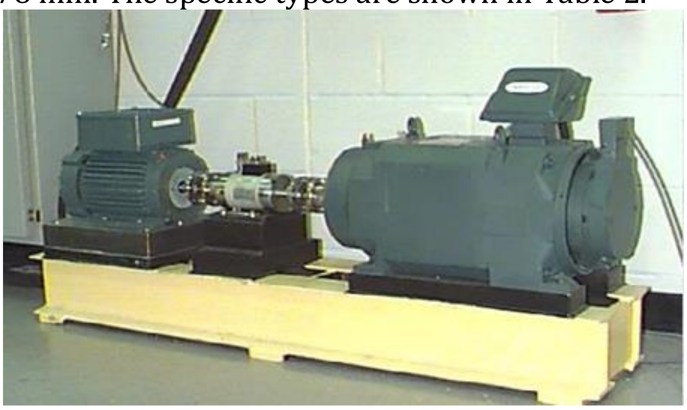

Figure 2. Bearing test bench of Western Reserve University

Table 2. Dataset division of Western Reserve University

Type	Fault diameter(mm)	Sample number
Nomal	0	800
Inner race fault	0.1778	400
Ball fault	0.1778	400
Outer race fault	0.1778	400
Total	/	2000

5.2. Xi'an Jiaotong University bearing dataset

In this section, the proposed model is verified by using the XJTU bearing acceleration test data published by Xi'an Jiaotong University, and the test bearing is LDK UER204 rolling bearing, and the experimental platform is shown in Figure 3.

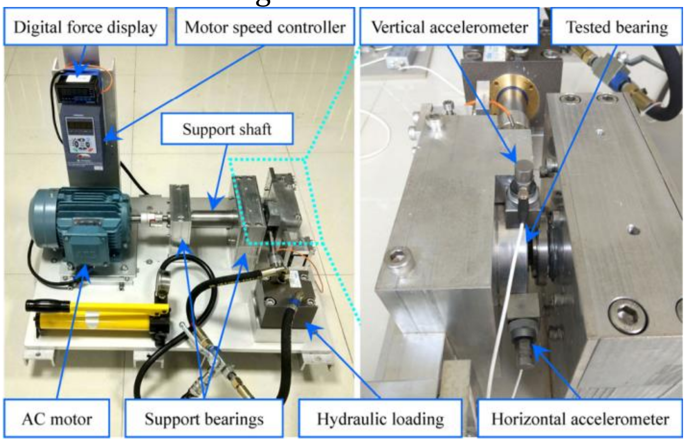

Figure 3. Bearing test bench of Xi'an Jiaotong University

The dataset is shown in Table 3, and two accelerometers are installed in the horizontal and vertical directions of the test bearing, with a sampling frequency of 25.6 kHz, a sampling interval of 1 min, and a sampling duration of 1.28 s. In this paper, the vibration data in the horizontal direction is used, and the data of three faulty bearings in the second working case and the normal signal of normal operation in the early stage are selected as the training set.

Table 3. Dataset division of Xi'an Jiaotong University

Type	Fault diameter(inch)	Sample number
Nomal	0	800
Inner race fault	0.007	400
Cage fault	0.007	400
Outer race fault	0.007	400
Total	/	2000

5.3. Experiment results

Ten experiments are carried out on the bearing datasets of Case Western Reserve University and Xi'an University of Technology, and the accuracy is shown in Figure 4. The highest accuracy rate can reach 96.3% on the bearing dataset of Xi'an University of Technology, but the variance is slightly larger than that of Xi'an University of Technology. The dataset of Western Reserve University is more ideal, and the accuracy is more stable. The average accuracy of these methods is more than 80%, which proves the effectiveness of this method.

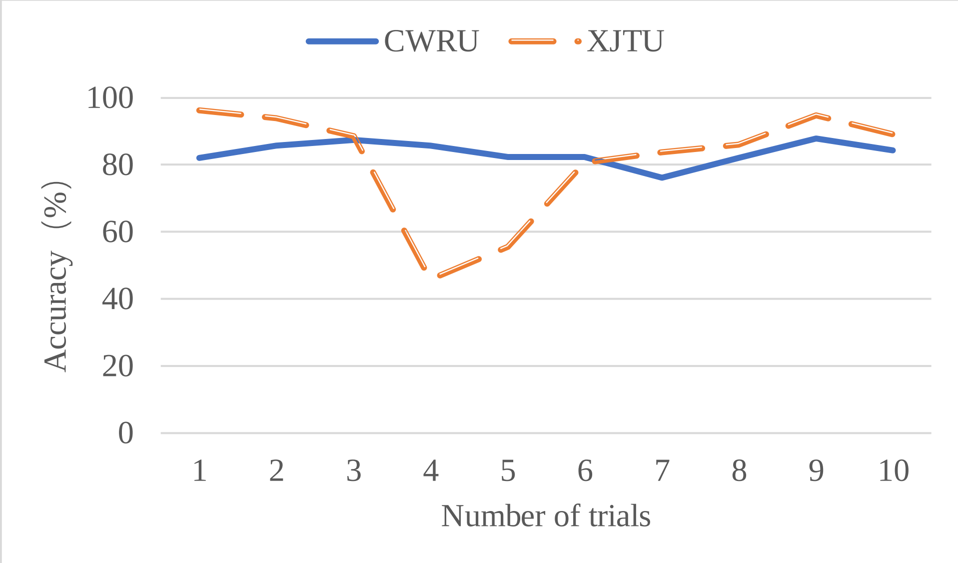

Figure 4. The recognition accuracy

6. Conclusion

In this paper, a new fault detection scheme based on graph neural network based on Minkowski similarity is proposed to solve the problem of bearing fault diagnosis. Because the amplitude and intensity of the characteristic signal are very small, its characteristics are extremely inconspicuous, and it is easy to be masked by system interference and noise, which is difficult to detect by traditional methods. To solve this problem, we design a new graph neural network structure, which is specially designed for unsupervised fault detection. Firstly, the *M* similarity algorithm is used to convert the 17 feature matrices of the vibration signal into the graph data required by the GNN, and then the feature matrix and the graph data are input into the GNN for training, and finally the experiments are carried out on the bearing datasets of Case Western Reserve University and Xi'an Jiaotong University, which validates the effectiveness of the proposed method in this paper.

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