Exploiting graph neural network with one-shot learning for fault diagnosis of mechanical equipment

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Abstract. For the classification of mechanical fault diagnosis, a graph neural network (GNN) method with one-shot learning is proposed. Convolutional Neural Network (CNN) is used to extract the feature vectors and One-Hot coding from images of Fault diagnosis of mechanical equipment. Inputting feature vectors and One-Hot coding into GNN, according to the Adjacency Matrix between vertices in the Graph, and is used for classification and inference. The method with one-shot learning is used for fault diagnosis classification. Through the fault classification for the industrial robot RV reducer and public data set CWRU pictures, the effectiveness of the method is verified. Five categories are used for fault diagnosis and classification in RV Reducer of the industrial robots. 80 categories are used in the public data set CWRU, and 55 categories are used as the training set. GNN is employed to spread the label information from the supervised sample of the unlabeled query data. The large-scale dataset can then be used as baseline classes to learn transferable knowledge for classifying novelties with one-shot samples. The one-shot learning with graph neural network GNN significantly improves the classification accuracy. The results show that the proposed method is superior to other similar methods and has a substantial potential for improvement in Fault diagnosis of mechanical equipment.

Keywords: Fault diagnosis; Graph neural network; One-shot learning; bearing; Industrial robot

1. Introduction
The early detection and diagnosis of mechanical equipment failure are essential to avoid catastrophic accidents[1]. For the classification of fault diagnosis of mechanical equipment, a large number of labeled image data is needed in the past, but sometimes the field is challenging, and experts with relevant experience are needed to label the data. This process is time-consuming and laborious. In this way, only a few pictures of each class need to be labeled by using one-shot Learning. Marking a few images in each category can automatically mark the remaining large numbers of images with high accuracy [2].

Because of the advantages of GNN in representing the sample relationship within and between classes, it has been widely concerned by researchers in recent years. The general graph structure cannot be directly applied to CNN, and a special graph convolution operation is required to get the hidden graph structure behind it. GNN is able to shift distance measures by the Euclidean Space and Non-Euclidean Space. Its structure is composed of nodes and edges, where each node has said a sample image, produced
by the node adjacency matrix is expressed as the side, the relationship between the sample and by iteratively the execution node characteristics and the relationship between node updates, from the label information on the supervised sample will be spread to the unlabeled query data. In this way, the sample image without the label can be predicted to achieve image classification task[3, 4].

This paper is based on the deep feature learning of CNN and GNN to obtain more representation attribute features. The GNN is used to understand the node features and the adjacency matrix between nodes (the measure of similarity) and other relevant information. Based on the deep learning of multi-source high-level representation features, the fault causes of mechanical equipment can be accurately located [5]. Experimental results show that our method is more competitive in fault diagnosis by comparing with the other one-shot learning methods. In this paper, the GNN of the one-shot learning method is proposed to carry out mechanical fault diagnosis and classification [6].

There are two main contributions to the present work. On the first hand, one-shot learning is applied in mechanical fault classification and diagnosis. In One-Shot Learning, there is less training sample data for each category. If a multi-classification model is trained directly, it will be unable to train adequately due to the small number of samples of each category of mechanical equipment. One of the advantages of GNN is that it can do information diffusion through the connection between nodes. If each sample is regarded as a node in the graph, and the edge between nodes is a measure of their distance, then the label information of the existing label samples can be selectively spread to the most similar samples that need to be predicted according to the similarity between nodes. On the other hand, this paper is based on the one-shot learning method of meta-learning and then uses GNN to spread the label information from the supervised sample to the unlabeled query data. The large-scale dataset can then be used as base classes to learn transferable knowledge for classifying novelties with one-shot samples.

2. Methodology
In the first section, the one-dimensional signals of mechanical equipment are transformed into two-dimensional pictures by short-time Fourier transform (STFT). In the second section, feature vectors are extracted by CNN. The third section is to input the feature vector into the GNN and to apply the GNN to the learning with the one-shot sample. Finally, the prediction results are obtained for the classification of Fault diagnosis of mechanical equipment.

2.1. Transforming one-dimensional signal into two-dimensional image by STFT
Because one-dimensional data lacks frequency-domain signal, it is necessary to use short-time Fourier transform to transform one-dimensional data into two-dimensional data [7, 8].

The steps of STFT for the original signal x(t) are as follows:
First move the window to the starting point of the signal. At this time, the center position of the window function is at t=2_0. And the signal is windowed:

\[ y(t) = x(t) * w(t - 2_0) \] (1)

Then perform the Fourier transform:

\[ X(\omega) = F(x(t)) = \int_{-\infty}^{+\infty} x(t) * w(t - 2_0)e^{-jwt}dt \] (2)

Thus, the spectrum distribution X(\omega) of the first segmented sequence is obtained. In real applications, since the signal is a discrete point sequence, what we get is a spectrum sequence X[N].

For the convenience of expression, we define the function here, which represents the spectrum result after transformation of the original function at the center of the window function, namely:

\[ S(\omega, 2) = F(x(t) * w(t - 2)) = \int_{-\infty}^{+\infty} x(t) * w(t - 2_0)e^{-jwt}dt \] (3)

As shown in Fig. 1, Repeat the above operation by constantly sliding the window and FFT, and finally get the spectrum results of all the segments from 2_0 to 2_N, and finally we get S, which is the result of STFT transformation. Thus, the one-dimensional data is converted into the picture form of the two-dimensional data.
2.2. Using CNN to extract feature vectors

The actual process of feature extraction (training) and matching feature (recognition) by CNN is the dot product of filters with different weight parameters and the input region block. The convolutional layer and the pooling layer can extract image features, and finally determine the parameters of the convolutional kernel through backpropagation to obtain the final features, which is a rough process of CNN feature extraction [9]. The size of one batch is [image-channel, batch-size, image-h], each sample is an image, including n-way * n-shot supported samples and a query sample.

2.3. Fault classification using graph neural network learned with one-shot learning

GNN is a graph model formed by many nodes and edges. It maps every image in the training data to a vertex on the graph. Through training, it obtains the adjacency matrix between the vertices in the graph and uses it to classify and infer. In this paper, each node represents an image, and the weight of each edge represents the relationship between the two images (distance or similarity) [10]. Specific weight calculation process:

$$\overline{A}^{(k)}_{i,j} = \varphi_{\theta}(x_{i}^{(k)}, x_{j}^{(k)}) = \text{MLP}_{\theta}(\text{abs}(x_{i}^{(k)} - x_{j}^{(k)}))$$

(4)

As shown in Fig. 2, it is learned by a nonlinear combination of the absolute differences between two node features. By this architecture, the symmetric distance characteristic is satisfied by construction $\varphi_{\theta}(a, b) = \varphi_{\theta}(b, a)$, and it is easy to learn its own distance characteristic $\varphi_{\theta}(a, a) = 0$, and output the corresponding weight value.
Softmax each row of the computed pass the data and transformation to Graph Conv. Gc apply these transformations to embedding and then go through a fully connected layer and LeakyRelu Generate a new embedding to ensure that the sum of the weights between each node and all other nodes is 1, and then after the adjacency matrix is obtained, GNN can be used to calculate the next layer of the network to complete the GNN transfer. The calculation process is as follows.

\[ x_l^{(k+1)} = Gc(x_l^{(k)}) = \rho \left( \sum_{B \in A} Bx_l^{(k)} \theta_{B,l}^{(k)} \right), \ l = d_1 \ldots d_{k+1} \]  

The accumulation symbol indicates that the adjacency matrix B can adopt a variety of calculation methods, and add them together. According to this formula, the update rule of the node feature can be obtained.

As shown in Fig. 3, due to the denseness of the edges in the graph, the depth is simply interpreted as giving the model more expressive power. However, there are only two cases in this paper: the weight of the connection between the node and itself is 1, and the weight of the connection with other nodes is \( \overline{A}_{i,j}^{(k)} \). In the training process, it is also necessary to change the weight of each layer of the network. The input \( V^{(k)} \) and the output of the Gc block are cascaded to form the lower-level network input \( V^{(k+1)} \), (this step is not required for testing).

![Graph Neural Network illustration](image)

The initial point feature is defined as

\[ x_i^{(0)} = (\phi(x_i), h(l_i)) \]  

Where \( \phi(\cdot) \) (a CNN) is a way to extract semantic features from the image, and \( h(\cdot) \) represents the translation of the tag into a one-hot vector.

The final loss function

\[ \min \frac{1}{L} \sum_{l=1}^{L} \ell(\Phi(\tau; \theta), Y_l) + R(\theta) \]  

\[ \ell(\Phi(\tau; \theta), Y) = -\sum y_k \log P(Y = y_k | \tau) \]  

Where \( \Phi(\tau; \theta) = P(Y | \tau) \), the predicted label is obtained through maximum likelihood estimation.

By using GNN and small one-shot learning in meta-learning, it can be applied to the fault diagnosis of mechanical equipment. The details are illustrated in Fig. 4 and summarized below.
3. Results and discussion
Siamese Net, SAE+RF and GNN were used to classify the industrial robot data. Tab. 1 shows the comparison of the different models. Obviously, GNN had the highest classification rate each time (96.43% on average). The accuracy of Siamese Net was 80.86%, and the performance of SAE+RF was the worst, only 31.17% on average. It was proved that GNN is the best classification method for industrial robot fault diagnosis. Conversely, SAE+RF was worst at classifying one-shot samples of data for fault diagnosis.

Table 1. Fault diagnosis accuracy of the comparisons on the industrial robot dataset

| Model     | Accuracy of each test (%) | Mean (%) |
|-----------|---------------------------|----------|
|           | 1 | 2  | 3  | 4  | 5  |      |
| Siamese Net | 79.40 | 83.25 | 79.30 | 82.05 | 80.30 | 80.86 |
| SAE+RF    | 29.87 | 29.63 | 31.43 | 32.00 | 32.93 | 31.17 |
| GNN       | 96.56 | 96.63 | 96.26 | 95.91 | 96.81 | 96.43 |

As shown in Tab.2, Similarly, Siamese Net, SAE+RF and GNN were also classified for CWRU dataset. The absolute advantage of GNN can also be found.

Table 2. Fault diagnosis accuracy of the comparisons on the CWRU dataset

| Model     | Accuracy of each test (%) | Mean (%) |
|-----------|---------------------------|----------|
|           | 1 | 2  | 3  | 4  | 5  |      |
| Siamese Net | 81.20 | 82.10 | 81.60 | 81.05 | 81.90 | 81.57 |
| SAE+RF    | 24.67 | 24.89 | 25.56 | 22.22 | WRU   | 24.62 |
| GNN       | 95.42 | 95.39 | 96.29 | 96.27 | 96.54 | 95.98 |

Fig 4. An overview of the proposed approach for classification of Fault diagnosis of mechanical equipment
4. Conclusions
A classification method for fault diagnosis of mechanical equipment is proposed in this paper. This method can improve the classification accuracy of fault diagnosis. The main contributions of this paper can be summarized as follows: First, the application of small sample research and learning methods in mechanical fault classification and diagnosis. In one-shot Learning, the training sample data of each category is less. One of the advantages of GNN is that information can be diffused through the connections between nodes. If each sample is regarded as a node in the graph, and the edge between the nodes is a measure of their distance, then the existing label can be used. According to the similarity between the nodes, the label information of the samples is selectively diffused to the most similar samples that need to be predicted. In the second part, a novel fault recognition model is constructed. Two different networks (CNN, GNN) carry out joint training examples. One is the general image convolutional neural network to extract the image feature expression; The other is the convolutional graph neural network, which completes the graph learning by constructing Adjacency Matrix on the characteristic difference of nodes.

Acknowledgments
This work is supported by the National Natural Science Foundation of China (51905058), Natural Science Foundation of Chongqing(cstc2020jcyj-msxmX0182,cstc2019jcyj-zdxmX0013), Key Project of Technology Innovation and Application of Chongqing(cstc2019jcsx-fxydX0077), Research Start-Up Funds of Chongqing Technology and Business University (1856018, 1752042), Key Research Platform Project of Chongqing Technology and Business University (ZDPTTD201918). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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