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Research on Industrial Robot Faults based on Graph Convolutional Neural Network

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Abstract

Aiming at the fault diagnosis of industrial robots during operation in practical applications, a fault diagnosis method for industrial robots based on graph convolutional neural network (GCN) is proposed. First, an experimental platform is built to determine and collect the operation process of industrial robots. The angle rotation information of each joint in the joint is extracted. Secondly, feature extraction is performed on the collected angle information, a graph convolution network model is built, and faulty joints are identified after training the model. The six-axis experimental data set is divided into training set and test set according to the ratio of 8:2. The data size of each fault type in the test set is randomly allocated. The training set and verification set are sent to the graph convolutional neural network for training. The number of training times is set to 100 and the batch size is set to 64. The test results show that the model can converge well and remain stable after 8 times of training, and its test accuracy can reach more than 92.7%.

Keywords

Industrial Robot; Fault Diagnosis; Joint Delay; Graph Convolutional Neural Network.

1. Introduction

Industrial robots are known as the "Crown Pearl" of the manufacturing industry. As an important automation equipment in modern manufacturing, they integrate multi-disciplinary knowledge and multi-field technologies to assemble multiple parts into a complex electromechanical system. In the industrial site environment Performance degradation or failure may occur from time to time. Without a proper maintenance and upkeep program, financial losses and severe component damage can result.

Fault diagnosis methods based on artificial intelligence include not only knowledge-driven (knowledge-based) methods, including expert systems and qualitative reasoning; but also data-driven methods, including statistical process control, machine learning methods and neural networks, etc. [1], In recent years, with the rapid development of computer processing speed and the improvement of related theories, the research of neural networks has made great progress, especially in the field of deep learning [2].

In the field of fault diagnosis: Yan Huiyu et al[3] Proposed a transfer learning gear fault diagnosis method based on Transformer and Convolutional Neural Network (CNN); Wang Mengdi et al [4] Proposed a fault diagnosis method for RV reducer based on multi-source graph structure mining; Yang Jiasong et al [5] In order to solve the problem of bolt loosening at the joint joints of industrial robots, an electromechanical coupling model was established based on the robot joint structure, and the base bolt loosening fault was introduced to establish a system dynamics model of bolt loosening;

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He Dongkang et al [5] Aiming at the modal confusion phenomenon that occurs when the singular value decomposition (SVD) optimizes the local mean decomposition (LMD) method to extract the weak fault characteristic components of the vibration signal of the crossed roller bearing of industrial robots, an industrial robot crossover based on maximum resolution SVD and LMD is proposed. Roller bearing fault feature extraction method; Xu Tianyun et al[6] Aiming at the problem of unclear representation of the root crack of the planetary gear of the robot RV reducer during robot operation and difficulty in extracting the frequency and fault features, a method for identifying the planetary gear fault of the RV reducer that combines information entropy and variational mode decomposition is proposed. method.

This paper proposes a fault diagnosis method for industrial robots based on graph convolutional neural network (GCN) based on fault diagnosis of industrial robots during operation in practical applications and conducts experiments to verify the proposed model.

2. Experimental Verification

2.1 Experiment Process:

The process of industrial robot fault diagnosis based on GCN is shown in Figure 1. The framework is divided into four modules: signal preprocessing, feature extraction, graph generation and state recognition. As shown in Figure 1, first, signal preprocessing, and second, feature extraction: comprehensively considering the structural characteristics of the industrial robot, select the effective value, maximum peak value, sub-peak value, etc. to describe the amplitude, waveform, dynamic changes and other time domain characteristics of the signal. Third, build the graph convolution network. Finally, state recognition: input the target domain sample into the trained network to obtain the state recognition result.

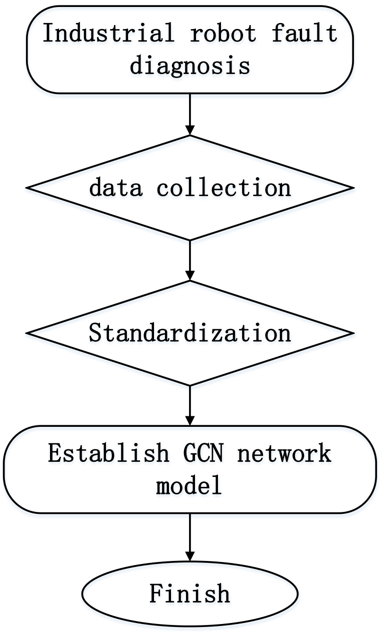

Figure 1. Industrial robot fault diagnosis flow chart based on GCN

2.2 Lab Environment:

In order to verify the effectiveness of the industrial robot joint fault diagnosis method based on graph convolutional neural network proposed in this article, the test was carried out through a self-made industrial robot fault test bench. The experimental platform and the connection method between the equipment are shown in Figure 2. The experimental platform consists of four parts: BN-R3 industrial robot, Siemens S7-1200 series PLC, data acquisition and storage system and data analysis system. The robot teaching pendant sends signals to the control cabinet to control the movement of the robot body. The PLC and the industrial robot communicate through the Modbus Tcp protocol. The PLC and the data acquisition and storage system transmit data through the Profinet protocol.

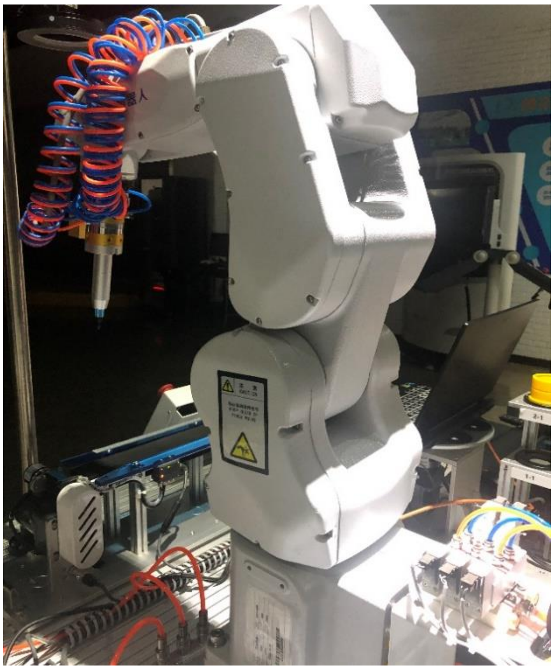

Figure 2. experiment platform

3. Experimental Verifications

3.1 Experimental Data Collection

In the experiment, the robot was set to the joint coordinate system, and the single axis rotated at the same angle for the two experiments before and after. For the convenience of observation, the robot running speed is set to low speed, and the single axis running speed is below 20°/sec. All parameters in the experiment are within the specified range. There are six groups of experiments in total, one for each axis, through PLC. Get angle information.

3.2 Experimental Data Preprocessing and Feature Extraction

The angular velocity data of the six joints are preprocessed, and every 28 data points are a feature. The extracted features are dimensionally reduced, and five features are selected: effective value, mean value, peak value, peak-to-peak value, and minimum value in the time domain. Perform feature layer data fusion. Finally, node classification is performed through the graph convolutional neural network and the diagnosis results are output.

3.3 Build Network Model

Table 1. Parameters used in the model training process

parameter name	Parameter Description
Training set: test set	8:2
optimizer	Adam
Batch size	64
training times Epoch	100
learning rate	0.0001
loss function	Cross Entropy Loss

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The model uses the parameters with the highest training and verification accuracy as the final parameters. The optimizer uses the Adam optimizer with fast convergence speed and stability, uses the cross-entropy loss function (Cross Entropy Loss), uses full connection to classify the target, and outputs the probability of each category. The parameters of the distribution model are shown in Table 1.

3.4 Experimental Results

100 subsamples were extracted from each data set, with a total of 700 subsamples in seven states, 80% of which were randomly selected as the training set and 20% as the test set. The data size of each fault type in the test set is randomly allocated, and the training set and verification set are sent to the graph convolutional neural network for training. The training process is shown in Figure 3. As can be seen from the figure, the model is trained 8 times. It can converge well and remain stable, and its test accuracy can reach more than 92.7%.

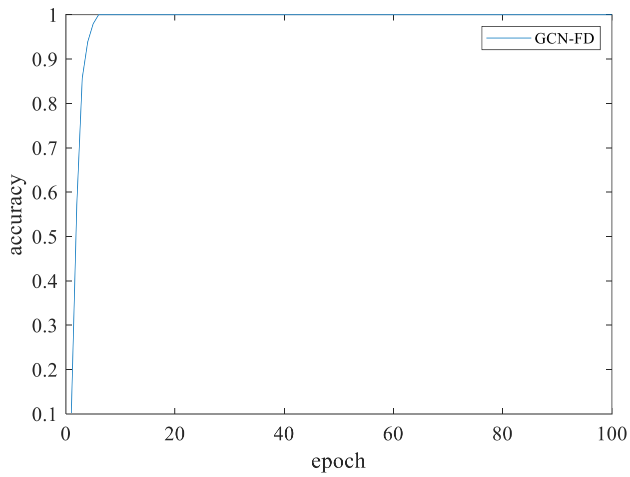

Figure 3. Model training process

4. Conclusion

Aiming at the problem of joint delay fault diagnosis and identification when the robot is moving, this paper proposes a GCN-FD-based joint fault diagnosis method for industrial robots. The established experimental platform is used to verify the fault diagnosis method based on the GCN-FD network model proposed in this paper. , the fault recognition rate of the GCN-FD network model reached 92.7%. In this study, the fault diagnosis method based on the GCN-FD network provides a new idea for industrial robot fault diagnosis.

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