Convolution Neural Network Based Fault Diagnosis of Induction Motor

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Abstract

Induction motors are one of the most important components for machine and industrial equipment in modern industrial applications. Therefore, it is necessary to develop a fault diagnosis system that detects the operating condition and fault of the induction motor early. This paper presents a induction motor fault diagnosis system using a CNN (Convolution Neural Network) model. In the proposed method, the fault diagnosis of the induction motor is performed by using the vibration signal data obtained from the induction motor experiment environment as the input value of the convolution neural network model. And then the fault diagnosis was made using convolution neural network. In this paper, fault diagnosis of normal state, rotor and bearing fault of induction motor is performed. From the experimental results, it is confirmed that the proposed method is suitable for diagnosis of rotor and bearing fault of induction motor.

Keywords: Induction motor, Convolution neural network, Rotor fault, Bearing fault, Fault diagnosis system

1. Introduction

Induction motors are one of the most important components for driving DC motors, rectifiers and DC motor systems and industrial equipment. However, the shutdown of the plant due to an unexpected induction motor fault results in significant economic losses. Therefore, it is necessary to develop a fault diagnosis system that detects the operating condition and fault of the induction motor early.[1]

Fault diagnosis is to detect faults in the system and to classify faults, which can be largely classified into model-based methods and non-model-based methods. In the model-based method, the fault of the system is diagnosed based on the mathematical model of the system, but it is not easy to obtain an accurate mathematical model due to the nonlinearity of the system.

Non-model-based methods include fault diagnosis based on measurements, experience, or physical reviews in the target system, and thresholding, expert system techniques, and neural networks.[2]

In particular, neural networks have advantages such as parallel processing ability, nonlinear function description and learning function, and there have been many studies to use neural network for trouble diagnosis based on this. However, the structure of the neural network model of the perfect connection layer can't learn the invariant property. This leads to a problem in that it can't be learned by extracting effective features from periodic vibration signals.[3]

In this paper, CNN model with local connectivity is used for fault diagnosis. And the vibration signals of three states normal, rotor fault and bearing fault are obtained from the induction motor, and the vibration

signals are used for fault classification. The performances of the proposed fault diagnosis method are verified through the experiment and simulation.

2. Experimental environment for fault diagnosis of induction motor
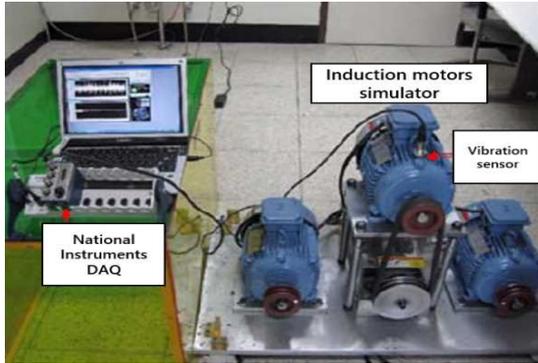

Fig. 1. Experimental set up.

For the fault diagnosis of the induction motor, a simulator was constructed as three three-phase induction motors that caused normal, rotor fault, and bearing fault as shown in Fig. 1. The induction motor located at the center is in the normal state. The induction motor located on the left side of the induction motor is in the state of rotor fault, and the induction motor located on the right side is in the state of fault of the bearing. We acquired the vibration data from induction motor by using NI9234 and vibration sensor.

(a) Rotor fault   (b) Bearing fault

Fig. 2. Fault types of induction motor.

As shown in Fig. 2, there are two types of faults occurring in induction motors: rotor fault and bearing fault. As shown in Fig. 2 (a), the rotor bar of the induction motor was punctured by a drill, and the bearing was worn by putting powder into the bearing as shown in Fig. 2 (b).

3. The proposed fault diagnosis method for induction motor

3.1. *CNN based fault diagnosis system*

The proposed fault diagnosis system consists of a vibration sensor part for measuring the vibration signal generated by the induction motor as shown in Fig. 3, a data collection part for digitizing and storing the vibration signal obtained from the vibration sensor, And a Convolution Neural Network (CNN) based fault classification unit which classifies the types of faults generated in the induction motor.
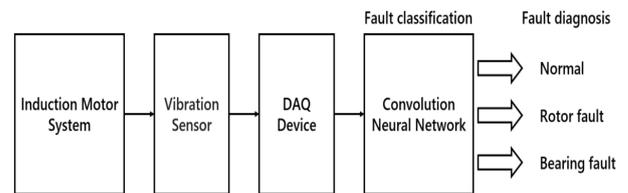

Fig. 3. Structure of the proposed fault diagnosis method.

3.2. *Convolution neural network*

Convolution neural network (CNN) is a model that integrates feature extraction and classification, which are separate from existing pattern recognition methods. CNN is basically composed of a plurality of convolution layer and a subsampling layer. [4] The structure of the CNN used in the induction motor fault system consists of one input layer, two convolution layers, two max polling layers and one fully connected layer and three output layers as shown in Fig. 4.
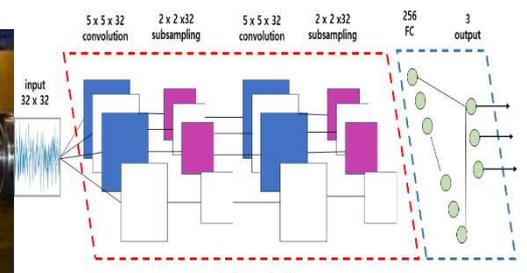

Fig. 4. Structure of the proposed CNN model.

The convolution layer extracts features from the input data. The convolution layer consists of a filter that extracts features. The filter detects the characteristics of the data and maps the detected features to the feature map. The extracted feature map applies the activation function. In this paper, Relu function is used as an activation function.[5]

The subsampling layer performs the process of reducing the dimension of the extracted feature map. There are various techniques for pooling. In this paper, It use the max pooling method which extracts the maximum value from the feature map. Using the max pooling technique reduces the size of the entire data, which reduces the amount of computation and extracts only the necessary data. [6]

In CNN, when the convolution layer and the max pooling layer are repeated, only the main features are extracted, and the extracted characteristics are transmitted to the Fully connected Layer. Since the convolution layer and the max pooling layer have two-dimensional data, they are transformed into a one-dimensional layer for transmission to the fully connected layer and then transferred to the output layer.

Softmax function was used for the output layer. softmax is used to transform the class classification problem, that is, the output from the previous layer, into the probability of each state when solving the state classification problem. Take the exponent on each output and divide by the normalization constant so that the sum is 1.

4. Simulation and Results

The simulation environment was implemented using Python 3.5 and Keras library in Windows 10 OS. The CNN model used in the simulation consists of an input layer with 1024 nodes, a first convolution layer and a max pooling layer, a second convolution layer and a max pooling layer, and finally, it consists of a fully connected Layer with 256 nodes and an output layer with 3 nodes. The two convolution layers and the fully connected layer use the activation function ReLU and the output layer uses the softmax function.

In order to test the performance of the proposed induction motor fault system, vibration signal data were acquired using a vibration sensor by artificially generating normal, rotor fault, and bearing fault in the experimental apparatus shown in Fig. 5. The vibration signal data can be obtained with 1024 data per 0.1 second. As a result, 1024 pieces of data are used as a model input. The data of the three states obtained from the experimental apparatus are shown in Fig. 5 (a), (b) and (c).

(a) Vibration data for normal state

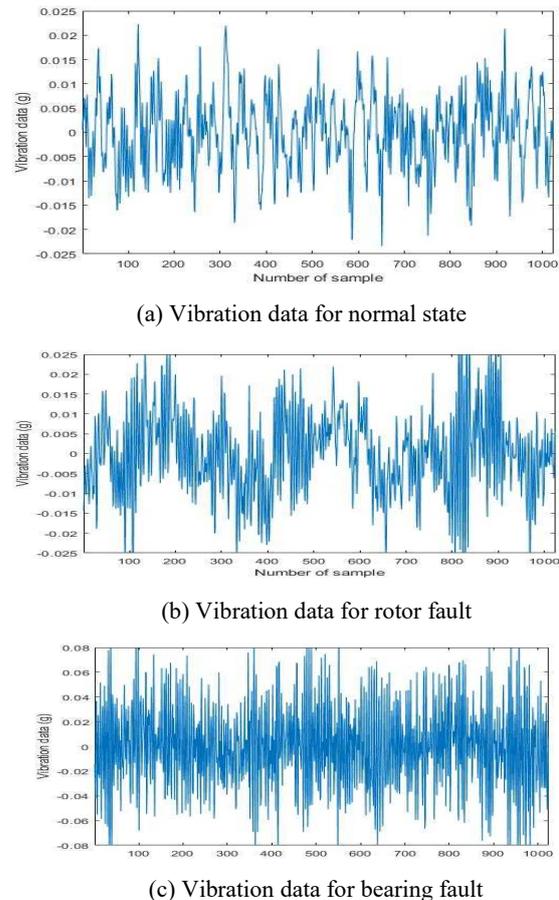(b) Vibration data for rotor fault

(c) Vibration data for bearing fault

Fig. 5. experimental data.

The data used for learning and verification data are data of normal, rotor fault and bearing fault state acquired from the experimental apparatus as shown in Table 1. For learning, 200 pairs of each state, that is, a total of 614,400 data, are used. The vibration data used in the learning was used without the frequency domain transformation. The epoch is 30. In the case of the test, data of 100 pairs for each state, that is, a total of 307,200 samples, were used. The results of the test are shown in Fig. 6, which shows two cases of fault diagnosis when the inverter changes from the normal state to the rotor fault state and when the inverter changes from the normal state to the bearing fault state. In Fig. 6, the x-axis represents the number of vibration data, and the y-axis represents the diagnostic value of the model. If classification result is 1, it is in the normal state. If 2 is output, it is the rotor fault state. If 3 is output, it is the bearing fault state.

Fig. 6 (a) shows the simulation result when the rotor is changed from the normal state to the rotor fault state. It

can be confirmed that the model correctly determines the rotor fault state when the vibration signal inputted at the 102,400 samples changes to the rotor fault state. Fig. 6 (b) shows the simulation results when the normal state changes to the bearing fault state. It can be confirmed that the model accurately determines the fault state of the bearing when the vibration signal inputted at 102,400 samples changes into the bearing fault state.

Table 1. The data pares for simulation.

Induction motor state	Number of training data	Number of test data
Normal	204,800	102,400
Rotor fault	204,800	102,400
Bearing fault	204,800	102,400
Total	614,000	307,200
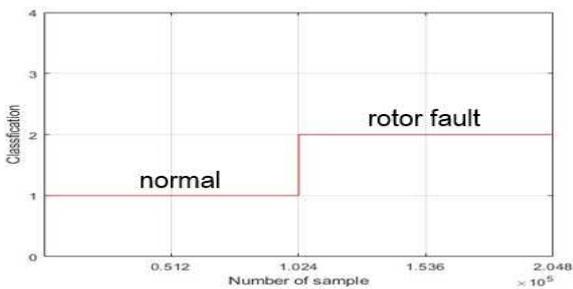
(a) Result of rotor fault diagnosis
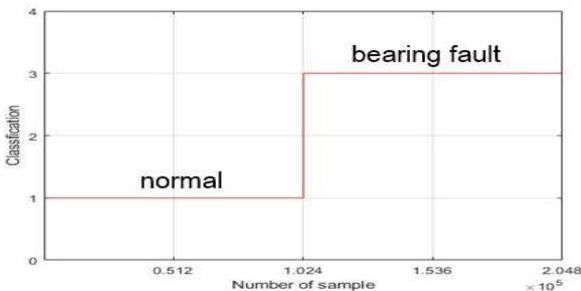
(b) Result of bearing fault diagnosis

Fig. 6. Result of the Induction motor fault diagnosis.

5. Acknowledgment

6. Conclusion

In this paper, an induction motor fault diagnosis system using CNN was proposed. In the proposed method, the fault diagnosis of the induction motor was performed by using the data obtained from the simulator as the input of CNN. As a result of the simulation, it was confirmed that the state of the motor was completely diagnosed by the motor data obtained from the simulator and the fault diagnosis can be performed without frequency domain transform process. The further study will need to apply the proposed method to the industrial equipment.

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