A CNN Based Approach with Identity Mapping Module for Mechanical Fault Diagnosis of High Voltage Circuit Breaker

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Abstract. In order to improve the accuracy and generalization of mechanical fault diagnosis of high voltage circuit breaker, a CNN with identity mapping module based approach is proposed. Six acceleration sensors are installed at specific positions of the circuit breaker to collect comprehensive vibration signals. A mechanical fault diagnosis model is established based on convolution neural network with identity mapping module. After preprocessing such as down sampling and data splicing, the input signals are analyzed to extract feature information and identify mechanical fault. The experimental results show that the proposed method has better performance in mechanical fault detection compared with traditional CNN method.

1. Introduction

Mechanical faults and electrical control circuit faults are the main faults of high-voltage circuit breakers [1]. Analyzing the vibration signal when the circuit breaker is operating is an important way to diagnose its mechanical faults. However, existing studies are mostly based on the data collected by a single acceleration sensor, which limits the further improvement of fault identification accuracy due to incomplete vibration information. In addition, in previous studies based on machine learning methods, fault features of signals need to be extracted manually. The feature extraction method highly relies on expert experience, resulting in the weak generalization of the model [2, 3].

As a typical deep learning model, Convolutional Neural Network (CNN) has been used in the field of bearing defects detection [2, 4], transformer oil dissolved gas analysis [5] and discharge pattern identification [6], etc. While CNN is seldom used for mechanical fault diagnosis of circuit breakers. This paper proposed a mechanical fault diagnosis method of high-voltage circuit breaker based on CNN with identity mapping. The acceleration sensors installed at different positions obtain the vibration signals. The neural network automatically mines the fault features and identifies the fault. This method can effectively overcome the over-fitting problem caused by the increase of the hidden layers in the traditional CNN, and give full play to the advantages of CNN in extracting image features.

2. Construction of identity mapping CNN

2.1. CNN with Improved Network Structure

With the increase of convolution layers, the traditional convolution neural network is prone to the problems of "degradation" and "vanishing gradient". He Kaiming from Microsoft Research proposed the identity mapping model [7]. By adding a direct connection channel between the network layers, the data from the shallow convolution layer can reach the deep convolution layer directly. This model
can protect the integrity of information, simplify the learning objective and difficulty, and significantly improve the training accuracy of the multi-layer CNN.

The structure of the convolutional neural network established in this paper is shown in Figure 1. The main structure of the network consists of ten layers: one input layer, five convolutional layers (C1~C5), one pooling layer (P1), two fully connected layers, and one output layer. There are two identical mapping channels: P1’s output to C3’s output and C4’s input to C5’s output. The activation function is ReLU. BatchNorm operation keeps the input of each layer in the same distribution during the training process. The dropout method is used in the training process of the fully connected layers.

2.2. Process of Fault Diagnosis

The process of identifying the mechanical fault of the circuit breaker by using the method proposed in this paper is shown in Figure 2. The specific steps are as follows:

a. Preprocess the original vibration signal, including data amplification and data splicing.

b. Divide the whole data into a training set, a verification set, and a test set.

c. Network parameters such as neuron weight and bias are adjusted according to the training set, and the super parameters such as learning rate are adjusted according to the verification set. During the training, the network will output the accuracy of the model on the verification set. After completing the training, the model will run on the test set and show the results.
3. Data acquisition and preprocessing

3.1. Fault Simulation and Vibration Signal Acquisition

In this paper, the research object is a 252kV outdoor porcelain column type SF6 circuit breaker with a CT-26 spring operating mechanism. Normal states and 12 types of faults in 5 categories are simulated, as shown in Table 1. The sampling rate is 200kHz and the sampling duration is 500ms. The installation positions of the six acceleration sensors are shown in Table 2.

| Fault type | Simulation effect | Simulation method | test times |
|------------|-------------------|-------------------|------------|
| Normal (first test) | -- | -- | 50 |
| Normal (second test) | -- | -- | 10 |
| Opening trip spring fatigue | Circuit breaker fault caused by opening trip spring fatigue | Mode 1: Replace the opening trip spring with a 2mm shorter one with constant elastic coefficient | 30 |
| | | Mode 2: Replace the opening trip spring with a 3mm shorter one with constant elastic coefficient | 30 |
| Pawl return spring fatigue | Circuit breaker fault caused by pawl return spring fatigue | Mode 1: Replace the pawl return spring with a 2mm shorter one with constant elastic coefficient | 30 |
| | | Mode 2: Replace the pawl return spring with a 3mm shorter one with constant elastic coefficient | 30 |
| Electromagnet jamming | Circuit breaker fault caused by electromagnet jamming | Hanging load 1 (3 nuts) | 30 |
| | | Hanging load 2 (6 nuts) | 30 |
| Opening and closing spring fatigue | Circuit breaker fault caused by opening and closing spring fatigue | Opening spring stretching 10mm | 20 |
| Temperature rise of coil | Circuit breaker fault caused by temperature rise of coil | Coil temperature rising 8 degree | 20 |

Table 2. Installation of vibration sensors

| Sensor number | Installation position |
|---------------|-----------------------|
| 1             | Above the opening electromagnet |
| 2             | Above the closing electromagnet |
| 3             | Near opening electromagnet |
| 4             | Near closing electromagnet |
| 5             | Near opening spring |
| 6             | Near closing spring |

As the vibration events of circuit breaker closing are much more abundant than that of circuit breaker opening, the closing signal is selected for analysis.

3.2. Data Preprocessing

In order to meet the demand of the Convolutional Neural Network for the number of training samples and suppress the over-fitting phenomenon, this paper adopts the method of down-sampling to amplify the data. Since an error of 5% of the sampling frequency for the acceleration sensor used in the...
experiment is 0.7~9000Hz, we set the down-sampling frequency of the original vibration signal to 10kHz. This action expands the number of training samples by 20 times.

Since vibration signals are one-dimensional time-series signals and can't match for the input format of CNN, we spliced them into a two-dimensional data array, as shown in Figure 3. This method can effectively preserve the position relation of time-domain characteristics for different vibration signals.

![Figure 3. 1-D signals spliced into 2-D signal](image)

### 4. Diagnostic process and results analysis

#### 4.1. Division of set

The verification set and the training set include the same type and degree of fault sample. The proportion of the verification set to the training set is 4:1. Considering the difficulty of obtaining the actual data of different fault types, the test set uses the simulating data with the same fault type and different fault severity as that in the training set. The training set, the verification set, and the test set are shown in Table 3.

| Training and verification sample type | Training set size | Verification set size | Corresponding test sample type | Test set size |
|--------------------------------------|-------------------|-----------------------|-------------------------------|---------------|
| Normal (first test)                  | 800               | 200                   | Normal (second test)          | 200           |
| Opening trip spring fatigue          | 480               | 120                   | Opening trip spring fatigue   | 600           |
| (mode 1)                             |                   |                       | (mode 2)                      |               |
| Pawl return spring fatigue           | 480               | 120                   | Pawl return spring fatigue    | 600           |
| (mode 1)                             |                   |                       | (mode 2)                      |               |
| Electromagnet jamming                | 480               | 120                   | Electromagnet jamming         | 600           |
| (hanging load 1)                     |                   |                       | (hanging load 2)              |               |
| Closing spring stretching 10mm       | 320               | 80                    | Closing spring stretching 15mm| 400           |
| Opening spring stretching 10mm       | 320               | 80                    | Opening spring stretching 15mm| 400           |
| Coil temperature rising 8 degree     | 320               | 80                    | Coil temperature rising 16    | 400           |
|                                      |                   |                       | degree                        |               |

#### 4.2. Diagnostic process

This paper builds a deep learning environment based on the TensorFlow framework. The input layer is 6×5000 two-dimensional data. The kernel size in C1 ~ C5 layers is 3×3. The pooling size is 2×2 in the P1 layer. The stride of each convolutional layer is 1. The number of convolutional kernels is 64. The first fully connected layer contains 64 neuron nodes, and the second fully connected layer contains 128 neuron nodes. Finally, the classification results are output by the Softmax regression classifier. During the training, the cross-entropy loss function is used to calculate the training error. The batch size is 10, and the initial learning rate is 0.001. AdaGrad optimization algorithm is used to adjust the learning rate. L2 regularization constraints are joined in model training.

In the experiment, every 16 samples of training set are packed into a minibatch, and input to the module for training. Every time a minibatch has been trained, the accuracy is recorded. Every time the total samples have been trained in the experiment (epoch), the model accuracy of verification set is measured. Five epochs are run totally. During the training, the training accuracy and cross-entropy
loss are tracked and collected, and corresponding curves are made, as shown in Figure 4. The accuracy curve in the training set is shown in Figure 4(a), and the accuracy curve in the verification set is shown in Figure 4(b). The horizontal axis shows the minibatch numbers.

As can be seen from Figure 4, under the conditions of this experiment, the model accuracy on the training set stabilizes at more than 99% when 100 minibatch training are complete. And the accuracy on the verification set stabilizes at 100% after three tests.

4.3. Comparison and analysis with other methods
At present, the CNN network structure for diagnostic analysis model is mostly LeNet-5 structure without identity mapping module. Ref. [2], [3], [5], [6] all use this network structure (hereinafter referred to as method 2) for diagnosis and identification. Ref. [8] extracted the amplitude of the waveform difference interval as a feature and used the WSVM classifier, which is a kind of mechanical fault diagnosis method with high accuracy and fast training speed (hereinafter referred to as method 3), but the feature extraction relied on artificial design.

Three methods are verified on the test set, and the results are shown in Table 4. The method proposed in this paper has the highest recognition rate in all kinds of faults, reaching 100% accuracy. Despite recognizing some samples of opening trip spring fatigue as that of electromagnet jamming, method 2 can identify other mechanical fault correctly. Method 3 has errors in the identification of opening trip spring fatigue, pawl return spring fatigue, Opening and closing spring fatigue and Electromagnet jamming, resulting in the worst accuracy. Through comparison, it can be concluded that the method proposed in this paper has the best generalization, which can extract the characteristics of multiple signals independently and accurately identify the faults of various mechanical structures of the circuit breaker, such as electromagnet, tripping mechanism, closing mechanism and opening mechanism. When identifying the faults similar to the training model, it can still classify the faults accurately. The recognition rate of method 2 is close to that of method 3 in the verification set, and the recognition effect of method 2 is better in the test set, which shows that CNN method has some advantages in generalization over artificial feature extraction method.

|                  | The proposed method | method 1                  | method 2                  |
|------------------|---------------------|---------------------------|---------------------------|
| Normal           | Normal (100%)       | Normal (100%)             | Normal (100%)             |
| opening trip spring fatigue | opening trip spring fatigue (100%) | Electromagnet jamming (6.7%) | Electromagnet jamming (3.3%) |
| Pawl return spring fatigue | Pawl return spring fatigue (100%) | Electromagnet jamming (96.7%) | Electromagnet jamming (3.3%) |
| Electromagnet jamming | Electromagnet jamming (100%) | Electromagnet jamming (100%) | Electromagnet jamming (96.7%) |
| Closing spring stretching | Closing spring stretching (100%) | Closing spring stretching (100%) | Closing spring stretching (100%) |
5. Conclusion
This paper proposes a mechanical fault diagnosis method for high-voltage circuit breakers based on CNN with identity mapping, which can extract the characteristics of multiple vibration signals independently and realize the accurate identification of simulated mechanical fault of circuit breaker.

a. The model in this paper can integrate the information collected by multiple sensors and accurately identify the mechanical fault of high-voltage circuit breaker.

b. Compared with the method of manual extraction of fault features, this method relies less on signal processing technology and fault diagnosis experience and has stronger generalization.

c. Compared with the traditional CNN without identity mapping module, the network structure of the model in this paper is more reasonable and the recognition accuracy is higher.

d. The training and test samples in this paper came from simulated mechanical faults of different severity of the same type while the previous researcher often take samples from identical faults. Compared with them, our method improves the model inspection standard.

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