Research on Transformer Condition Recognition Based on Acoustic Signal and One-dimensional Convolutional Neural Networks

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Abstract. To solve the problem of transformer condition recognition, this paper propose a transformer condition recognition method based on acoustic signal and One-dimensional Convolutional Neural Networks(1D-CNN). In order to verify the effectiveness of 1D-CNN algorithm in the field of transformer condition recognition, a platform for acquisition of acoustic signals from a 500 kV transformer is built to carry out the acoustic signal acquisition test for four conditions of the transformer. The acoustic signal data sets are also made, and the 1D-CNN algorithm is used to calculate the recognition accuracy of the transformer conditions. According to test results, 1D-CNN algorithm, as a new structure of deep-learning algorithm, can properly classify acoustic signals of the transformer, and its classification accuracy is higher than those of FFT-BP, SVM, FFT-SAE and other algorithms. In order to explore the internal mechanism of 1D-CNN algorithm, in this paper, a t-SNE visual analysis is also conducted to reveal the performance of 1D-CNN algorithm.

1. Introduction

The transformer is a key device in the power system. Once a fault occurs, it will cause great damage to the safe and stable operation of the power system. Therefore, it is of great significance to monitor the condition of the transformer. At present, there are many researches on condition recognition, which can be divided into three categories by means of acquisition: condition recognition based on temperature, condition recognition based on vibration signal, and condition recognition based on acoustic signal.

The condition recognition based on temperature is mainly to monitor the internal oil temperature of the transformer with the temperature sensor. Literature⁴ monitors the internal oil temperature of the transformer and predicts the condition using the intelligent algorithm. Literature⁵ designs a set of transformer condition recognition system, which can send an alarm when the oil temperature is overloaded. The condition recognition based on vibration signal is mainly to use the vibration signal of the transformer surface in different conditions for condition recognition. Relevant researches are as
follows: Literature[3] recognizes the transformer fault condition using SVM algorithm and vibration signal; although the condition recognition method based on temperature and vibration signals has been applied to some extent, both temperature sensors and vibration sensors need to be installed inside or on the surface of transformers, which has certain limitations. However, the condition recognition based on acoustic signal does not need to contact with the transformer, which has great advantages. In Literature[4], the author acquires noise signal generated with the transformer and classifies the fault condition of the transformer.

The core algorithm of transformer condition recognition mainly consists of feature extraction and pattern recognition. Traditional feature extraction algorithms include Fourier transformation, wavelet transformation, empirical mode decomposition, and signal statistical features, etc. Traditional pattern recognition algorithms include BP neural network, SVM, Bayesian classifiers and so on. The advantage of the traditional condition recognition method is that the feature extraction method is simple and easy, but it proposes higher requirements on manual participation. It relies on manual extraction and expert knowledge in the field, and needs manual feature extraction and algorithm selection for different application environments, which is subjective to some extent[5].

In recent years, with the continuous development of deep learning algorithm, the application research of fault diagnosis technology based on deep learning method has started. CNN is a typical deep learning method developed in recent years. Its greatest advantage is that there is no need to manually select features. It has been widely used in computer vision, natural language processing and other fields. The paper designs a new 1D-CNN, and puts forward a transformer condition recognition algorithm based on acoustic signal and 1D-CNN. The algorithm omits the process of manual feature extraction with the traditional algorithm. Therefore, the raw data is directly sent to the 1D-CNN without preprocessing. Through the powerful feature extraction capability of the 1D-CNN, the nonlinear features hidden in the raw data are automatically extracted by use of the alternating convolution layer and pooling layer in the 1D-CNN, and the self-adaptive feature learning is completed in combination with the fully-connected layer, finally realizing the accurate classification of acoustic signals of transformer conditions.

2. Basic principle of 1D-CNN

2.1. CNN
A typical CNN usually includes the input layer, convolution layer, pooling layer, fully-connected layer, and output layer [6].

The input layer of CNN can process multi-dimensional data and standardize the input data in advance to improve the operation efficiency and learning performance of the algorithm.

The convolution is calculated for output of the upper layer for convolution layer, and the non-linear activation function is adopted to construct the output feature. The purpose of activation function is to map multi-dimensional features with originally indivisible linearity to another space, thus enhancing the linear separability of features. The mathematical model of convolution is described as:

\[
y^{(l+1)}_i (j) = K^l_i \ast x^{(l)} (j) + b^l_i
\]  

Wherein, \( K^l_i \) represents the weight of the i-th filter at the l-th layer, \( b^l_i \) represents the network offset of the i-th filter at the l-th layer, \( x^{(l)} (j) \) represents the j-th local input at the l-th layer, and \( y^{(l+1)}_i (j) \) represents the input in the j-th neuron at the i-th frame of the l+1-th layer.

The activation function transforms the logits value in a non-linear manner of each convolution. The ReLU function is adopted in this paper. When the input value is larger than 0, the derivative value of ReLU function is always 1, thus overcoming the diffusion of gradients. The formula of ReLU is as follows:

\[
d^{(l+1)}_i (j) = f(y^{(l+1)}_i (j)) = \max\{0, y^{(l+1)}_i (j)\}
\]  

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Wherein, $y_i^{(l+1)}(j)$ represents the output value of convolution, and $a_i^{(l+1)}(j)$ represents the activation value of $y_i^{(l+1)}(j)$.

The pooling layer takes the large matrix samples down to the small matrix through data downsampling, thus reducing the calculation and preventing overfitting. The formula of maximum pooling is as follows:

$$P_i^{(l+1)}(j) = \max_{(j-1)W+1 \leq t \leq jW} \{q_i^t(t)\}$$  \hspace{1cm} (3)

Wherein, $q_i^t(t)$ represents the value of the $t$-th neuron in the $i$-th feature at the $l$-th layer, $t \in [(j-1)W+1, jW]$, $W$ represents the width of pooling area, and $P_i^{(l+1)}(j)$ represents the value of the $j$-th neuron in the $i$-th feature at the $l+1$-th layer.

The fully-connected layer can integrate differentiated local information in the convolution layer or pooling layer to realize global optimization. The formula of a fully-connected layer is as follows:

$$z_i^{(l+1)}(j) = f(\sum_{i=1}^{m} \sum_{t=1}^{n} W_{i,0}^j a_i^t(t) + b_j^l)$$  \hspace{1cm} (4)

Wherein, $W_{i,0}^j$ represents the weight between the $t$-th neuron in the $i$-th feature at the $l$-th layer and the $j$-th neuron at the $l+1$-th layer, $z_i^{(l+1)}(j)$ represents the logits value of the $j$-th neuron at the $l+1$-th layer, $b_j^l$ represents the network offset, $a_i^t(t)$ represents the output value of the $t$-th neuron in the $i$-th feature at the $l$-th layer, and $f(\cdot)$ represents the activation function ReLU.

The softmax classifier is commonly used to output the classification label for the output layer. The softmax classifier is a common linear classifier, which is the generalization of a logistic regression classifier. The formula of softmax classifier is as follows:

$$\text{softmax}(z^o(j)) = \frac{e^{z^o(j)}}{\sum_{k=1}^{M} e^{z^o(k)}}$$  \hspace{1cm} (5)

Wherein, $z^o(j)$ represents the output value of the $j$-th neuron at the output layer, and $M$ represents the total number of categories.

2.2. Intelligent fault diagnosis method of 1D-CNN

Based on the basic principle of CNN, to solve the identification and application problems of acoustic signals of a transformer under different conditions, a new 1D-CNN structure is designed in this paper, as shown in Figure 1. The convolution network contains three convolution layers, three pooling layers, a fully-connected layer, and a soft max layer. The signal becomes a set of feature maps after passing the first convolution layer, and then down sampling is conducted through maximum pooling. In this way, the feature of the last pooling layer is connected with the fully-connected layer and transferred to the soft max layer through multi-layer convolution and pooling (picture for reference).

In this paper, the new 1D-CNN structure parameters used in the test are shown in Table 1. The structure consists of three convolution layers and pooling layers, and the size of the first, second, and third convolution kernels is 64*1, 32*1, and 16*1 respectively. The soft max layer has four outputs, corresponding to the four conditions of the test transform.
Table 1 1D-CNN Structure Parameters

| No | Network layer       | Convolution kernel size/step length | Number of convolution kernels |
|----|---------------------|-------------------------------------|-----------------------------|
| 1  | Convolution layer 1 | 64*1/1*1                           | 16                          |
| 2  | Pooling layer 1     | 16*1/2*1                           | 16                          |
| 3  | Convolution layer 2 | 32*1/1*1                           | 64                          |
| 4  | Pooling layer 2     | 2*1/2*1                            | 64                          |
| 5  | Convolution layer 3 | 16*1/1*1                           | 128                         |
| 6  | Pooling layer 3     | 2*1/2*1                            | 128                         |
| 7  | Fully-connected layer | 100                           | 1                           |
| 8  | Softmax layer       | 4                                  | 1                           |

3. Transformer condition monitoring test

The 500-kV transformer is used in the test. This group of test transformers has four conditions, including 20%, 40%, 80%, and 100% of current respectively.

Firstly, the platform for acoustic signal acquisition test under different transformer conditions is built. The test platform is shown in Figure 2, including a BK4189 test microphone, a BK3160 data acquisition system, and a portable computer for post-processing.
The time domain waveforms of acoustic signal of transformer under four conditions collected by the test platform are shown in Figure 3(a), and the corresponding frequency spectrums are shown in Figure 3(b):

![Time domain waveforms of acoustic signals](image1)

![Corresponding frequency spectrums](image2)

Figure 3 Time Domain Waveform and Frequency Spectrum of Acoustic Signal of Transformer under Four Conditions

Then, the sample dataset of transformer conditions is made. Every 2,048 points are regarded as a sample, and the acoustic signal of transformer under each condition contains 1,500 groups of samples, and label categories are added to form the condition sample dataset as shown in Table 2:

| Transformer condition | Number of samples | Label category |
|-----------------------|-------------------|----------------|
| 20% current           | 1500              | 0              |
| 40% current           | 1500              | 1              |
| 80% current           | 1500              | 2              |
| 100% current          | 1500              | 3              |
4. Test result analysis

4.1. Analysis on condition dataset results of transformer

4.1.1. Analysis on performance of 1D-CNN algorithm

First, analyze the accuracy of 1D-CNN algorithm with the change in number of iterations. The accuracy indicates the ratio of the number of samples correctly classified by classifier to the total number of samples for a given testing dataset. The performance of classification algorithm can be directly reflected by calculation accuracy.

Process the dataset in Table 2 with 1D-CNN algorithm, calculate the corresponding accuracy value obtained after each time of iteration, and finally draw the accuracy curve of 100 iterations, as shown in Figure 4:

![Figure 4 Accuracy Curve of 1D-CNN Algorithm](image)

According to the figure, with the increase of the number of iterations, the accuracy of 1D-CNN algorithm is on the rise. After 100 iterations, the accuracy can reach higher than 98%. Next, conduct visualization analysis on performance of 1D-CNN algorithm. The t-distributed Stochastic Neighbor Embedding (t-SNE) is a technology integrating dimensionality reduction and visualization, and it converts the high-dimensional Euclidean distance among data points into the conditional probability representing similarity. After the visualization algorithm maps the high-dimensional data to low-dimensional data, the points separated from each other in the high-dimensional space remain unchanged in the low-dimensional space. After learning convergence, t-SNE can project the dataset to a two-dimensional or three-dimensional space. To explore the internal mechanism of 1D-CNN algorithm proposed in this paper, conduct a visualization analysis with three-dimensional distribution on the acoustic signal features of the transformer after passing through a convolution layer by t-SNE visualization algorithm, as shown in Figure 5.

![Figure 5 Visualization Analysis](image)
In Figure 5(a), the time domain raw data of acoustic signal dataset of the transformer can hardly be separated; in Figure 5(b), the feature expression after passing through one convolution layer is still not completely separated, while the feature distribution has shown a trend of separation; in Figure 5(c), the feature expression obtained after passing 2 convolution layers can be gradually separated; in Figure 5(d), the feature expression obtained after passing 3 convolution layers can be completely separated, and the raw data of time domain converge in their corresponding areas respectively. From the
visualization results of Figure 5, we can see that 1D-CNN algorithm can classify the transformer acoustic signal.

4.1.2. Comparison of 1D-CNN algorithm and other algorithms
In this paper, we select FFT-BP, SVM, FFT-SAE and other algorithms to compare with 1D-CNN algorithm. FFT-BP, SVM and FFT-SAE algorithms are three common algorithms for classical algorithm and deep learning algorithm respectively. Among them, FFT-BP algorithm is to input the features of acoustic signals after transformation by FFT to BP network for classification, SVM algorithm is to conduct SVM classification for statistical characteristics of acoustic signals in time-frequency domain, and both algorithms are classical algorithms; FFT-SAE algorithm is to input the features of acoustic signal after transformation by FFT to SAE network for classification, which belongs to a deep learning method.

The comparison on the accuracy of FFT-BP, SVM, FFT-SAE and other algorithms and 1D-CNN algorithm is shown in Table 3:

| Algorithm | Accuracy |
|-----------|----------|
| 1D-CNN    | 99.0%    |
| FFT-BP    | 81.3%    |
| SVM       | 89.2%    |
| FFT-SAE   | 94.8%    |

Table 3 describes the classification of transformer acoustic signal datasets with different algorithms. The accuracy of 1D-CNN algorithm proposed in this paper, as a new deep learning algorithm, is obviously higher than FFT-BP, SVM and other classical algorithms, and also FFT-SAE deep learning algorithm.

5. Conclusion
As for the requirements of transformer condition recognition, in this research, we propose a transformer condition algorithm based on acoustic signals and 1D-CNN algorithm, and conduct a research with a certain type of transformer as the test object to validate the effectiveness of 1D-CNN algorithm in the transformer condition recognition area. The main contributions of this research are as follows:

1. We design a new 1D-CNN, and propose a transformer condition recognition method based on acoustic signals and 1D-CNN. The algorithm can automatically extract and classify the features of acoustic signal data.
2. We conduct a visualization analysis on 1D-CNN algorithm performance with t-SNE visualization algorithm, and explore the internal mechanism of 1D-CNN algorithm.
3. We compare the accuracy results of 1D-CNN algorithm with FFT-BP, SVM, FFT-SAE and other algorithms to validate the 1D-CNN algorithm, which has a higher accuracy as a new deep learning algorithm for structure.
4. The transformer condition recognition method proposed based on acoustic signals and 1D-CNN is expected to realize the valid recognition of transformer conditions.

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