Partial Discharge Pattern Recognition of Transformer Based on Deep Forest Algorithm

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Abstract. In order to improve the accuracy of pattern recognition of transformer partial discharge type, solving the current pattern recognition based on machine learning algorithm requires artificial extraction of description features, poor adaptability and low recognition accuracy. In this paper, the deep forest algorithm is introduced into the partial discharge pattern recognition of transformers. In this method, the partial discharge images collected by partial discharge inspection instrument are processed by gray-scale and bilinear interpolation as input of deep forest model. The feature extraction of PD images is realized by using multi-grained scanning structure, and the classification of PD is realized by using cascade forest structure as classifier. By setting up the partial discharge experiment platform of transformer, the algorithm is tested with the sample data obtained from the experiment, and the results show that the pattern recognition accuracy of this method is high, and the recognition accuracy increases with the increase of sample data.

1. Introduction

As a pivotal device of power system, power transformer plays the role of energy transmission and transformation in the power system, and its operating status is related to the safe and stable operation of the power system. The main reason of transformer failure is insulation deterioration, and partial discharge is an effective sign of transformer insulation deterioration. Different types of partial discharge have great differences in the damage degree of insulation, so it is of great significance to identify the type of partial discharge to evaluate the insulation condition of transformer [1-3].

At present the research on PD type recognition mainly focuses on feature extraction and classification recognition algorithm. The commonly used methods for extracting characteristic variables of PD signal mainly include statistical characteristic parameter method [4], waveform characteristic parameter method [5], fractal characteristic parameter method [6], moment characteristic parameter method [7] and wavelet characteristic parameter method [8]. In the field of partial discharge pattern recognition, the main methods focus on BP Neural Network, Support Vector Machine and K-Nearest Neighbour algorithm, and have achieved good classification effect [9-11]. However, traditional PD pattern recognition methods require artificial extraction of signals. The selection of these features is only set for specific data, relying too much on the method established by experts in the natural field for a certain problem, and lacking of good generalization, and several PD feature information will be lost in the feature extraction process.
Due to the large amount of graph or waveform data measured by PD, it is very difficult or even impossible to identify the PD time domain signal by using the traditional artificial feature extraction method or shallow neural network. In recent years, the emergence of deep learning technology in academia and industry has pointed out the direction to solve this problem [12-13]. Due to the significant advantages of deep learning in data feature extraction and pattern recognition, this paper proposes a method of automatic feature learning and pattern recognition of PD images collected by deep forest algorithm. This method avoids the defect of traditional PD pattern recognition method and provides a new idea for intelligent PD pattern detection.

2. Principle of deep forest algorithm

Deep forest algorithm is a supervised machine integration learning algorithm based on random forest (RF) inspired by deep learning theory and deep neural network [14]. As a kind of a certain depth integration based on decision tree classification algorithm, the depth of the forest algorithm to predict the classification process is divided into two stages: multi-grained scanning stage and cascade forest stage. The random forest algorithm, multi-grained scanning stage and cascade forest stage are introduced in the following sections.

2.1. Multi-grained scanning structure

In the deep forest algorithm, the multi-grained scanning stage is set to extract the sample features and to mine the features of the sample image as much as possible. It is defined as follows [14]: let $W = (X_N, v, b, l)$, Where, $X$ is the original input feature, $N$ is its dimension, $v$ is the scanning window dimension, $b$ is the scanning step size, and $l$ is the number of scanning windows. Then the number of features after scanning $r = (N-v)/b+1$.

2.2. Cascade forest structure

In the deep forest algorithm, cascading forest structure is used to process the data characteristics layer by layer, so as to enhance the representation learning ability of the algorithm and improve the accuracy of pattern recognition. It is defined as follows [14]: let $CF = \{z, F, t, c\}$, stands for cascade forest. Where, $z = \{1, 2,..., Z\}$ represents the series of cascade forests, each level contains $m$ forests $F$, $m = \{1, 2,..., M\}$. $F$ is random forest and completely random forest composed of $t$ decision trees respectively, $t = \{1, 2,..., T_m, Z\}$, $c = \{1, 2,..., C\}$ represents the category label of the sample.

In the training stage, each level of the cascade forest will generate the distribution vector of sample $x$, as shown in equation (1):

$$P_{(t,m)}^i(x) = (p_{1}^{(t,m)}(x), p_{2}^{(t,m)}(x), \cdots, p_{c}^{(t,m)}(x))$$

Where, $p_{c}^{(t,m)}$ is the probability that the sample $x$ calculated by each decision tree belongs to category $c$. Then, each forest will get its own estimation of the class distribution of sample $x$ based on this probability, expressed as equation (2):

$$V_{c}^m(x) = (V_{1}^m(x), V_{2}^m(x), \cdots, V_{c}^m(x))$$

Among them, $V_{c}^m(x) = T_m \sum_{i=1}^{T_m} p_{c}^{(t,m)}(x)$. Then, cascade forests combine the output results of each level with the original feature vector as the input of the next level of forests, which can be expressed as equation (3):

$$x \leftarrow (x, V_1(x), V_2(x), \cdots, V_c(x))$$

And so on, until the accuracy is no longer rising, stop training.

3. PD pattern recognition of transformer based on deep forest algorithm

3.1. Network structure design

In this paper, partial discharge inspection instrument is used to obtain the typical partial discharge time domain signal image, which is converted into grayscale image. Then, all images are scaled to 80x30 by
the bilinear interpolation algorithm, and finally the image pixels are normalized to between \([0, 1]\). On this basis, a deep forest model for transformer PD type identification is designed. The specific structure is shown in figure 1.

As can be seen from figure 1, firstly, a gray-scale image with the size of \(80 \times 30\) is input into the input layer, which serves as the input of multi-grained scanning structure of deep forest. As shown in figure 1, the image size is \(80 \times 30\), and the sliding window of \(9 \times 9\) will generate 1584 instances (that is, \(1584 \times 9 \times 9\) matrices). Then, the extracted instance model is used to train the Forest model, where Forest A is random forest and Forest B is completely random forest. For each instance, a two-dimensional class vector is obtained by training the forest model, and 1584 class vectors are generated for each forest. Finally, two classification vectors are spliced to form a 3168-dimensional feature vector as the input of cascade forest.

In cascade forest structure, each level obtains the processed eigenvectors from the upper layer, and uses the eigenvectors to generate new eigenvectors to transfer to the next layer. As shown in figure 1, the cascade forest adopts the 3168-dimensional eigenvector obtained after multi-grained scanning structure processing as the input. First, two 2-dimensional category vectors are obtained after two different types of forest model classification. Then, these two 2-dimensional category vectors are spliced with the original 3168-dimensional feature vectors to form the new 3172 feature vectors as the input vectors of the next layer. According to this method, the new eigenvector of 3168+2×2×(n-1) dimension will be output at the n-1st layer as the input of the nth layer. Finally, the category vector generated by the last layer is averaged, and the category corresponding to the maximum value is taken as the classification result of PD samples to complete partial discharge pattern recognition.

3.2. Flow chart of deep forest algorithm
The implementation process of the deep forest overall algorithm as shown in figure 2.
4. Analysis of experimental results

4.1. Defect model and experimental platform design

Partial discharge occurs due to the deterioration of transformer insulation structure due to manufacturing process or long-term operation, and its discharge forms mainly include corona discharge, surface discharge and air gap discharge. According to the characteristics of insulation structure inside the transformer, this paper designs and makes the three partial discharge models [15], as shown in figure 3.

![Figure 3. Three types of partial discharge experimental models.](image)

The experimental platform of partial discharge of transformer is built under the condition of low external disturbance, and the discharge signal of typical partial discharge fault model is collected by pulse current method. The experimental platform is shown in figure 4, including the power frequency high-voltage test control system and partial discharge detection system. The control system of power frequency high voltage test protection resistor is 10kΩ, capacitive voltage divider capacitor for 1000pf. The partial discharge detection system uses the HCPD-2622 digital partial discharge inspection instrument, and uses the pulse current method to detect the PD signal. The sampling frequency is 20MHz.

![Figure 4. Partial discharge experimental platform.](image)

4.2. PD pattern recognition results based on different features

Using the partial discharge experiment platform of transformer shown in figure 4, 205 images of each partial discharge type were collected, and a total of 615 images normalized to 80×30 size were taken as samples. The network structure model shown in figure 1 was used to train and test the samples. In order to ensure the objectivity of experimental results, images of each discharge type were randomly selected as training samples and test samples, and sample sets with training samples and test samples ratios of 0.7:0.3, 0.5:0.5 and 0.5:0.5 were established respectively.

Based on the above sample set, the features of PD signals are extracted by multi-grained scanning and sparse self-encoder, and the two different features are input into the RF ensemble classifier, SVM
ensemble classifier and BPNN ensemble classifier to identify PD patterns. The corresponding results are shown in Table 1.

Table 1. Recognition accuracy of partial discharge pattern based on different features

| Feature extraction method            | RF   | SVM | BPNN |
|-------------------------------------|------|-----|------|
| Multi-grained scanning              | 98.39% | 96.77% | 91.94% |
| Sparse self-encoder                 | 96.12% | 96.77% | 84.52% |

| Feature extraction method            | RF   | SVM | BPNN |
|-------------------------------------|------|-----|------|
| Multi-grained scanning              | 98.05% | 97.08% | 90.10% |
| Sparse self-encoder                 | 95.53% | 95.14% | 82.14% |

| Feature extraction method            | RF   | SVM | BPNN |
|-------------------------------------|------|-----|------|
| Multi-grained scanning              | 94.44% | 91.67% | 88.61% |
| Sparse self-encoder                 | 90.90% | 89.58% | 72.22% |

As can be seen from Table 1, for PD signals of different fault types, different classifiers are used in the same sample set. The PD pattern recognition accuracy based on multi-grained scanning to extract sample features is higher than that based on sparsely extracted sample features from encoder. The reason is that multi-grained scanning deep forest model has significant advantages in feature quantity extraction and can extract intrinsic information of data. Because the characteristic quantity contains rich discharge information, the classifier can comprehensively analyze the characteristics of samples, which makes the partial discharge recognition accuracy higher.

4.3. The result of classifier recognition

In the case of extracting PD features by multi-grained scanning method, the partial discharge pattern recognition accuracy of BPNN ensemble classifier, SVM classifier, RF ensemble classifier and cascade forest classifier is shown in Table 2.

Table 2. Recognition accuracy of partial discharge pattern based on different classifiers

| Classifier                | Sample set |
|---------------------------|------------|
| BPNN ensemble classifier  | 0.7:0.3    |
| SVM classifier            | 91.94%     |
| RF ensemble classifier    | 96.77%     |
| Cascade forest classifier | 99.07%     |
|                          | 0.5:0.5    |
|                          | 90.10%     |
|                          | 97.08%     |
|                          | 98.05%     |
|                          | 98.82%     |
|                          | 0.3:0.7    |
|                          | 88.61%     |
|                          | 91.67%     |
|                          | 94.44%     |
|                          | 96.53%     |

It can be seen from Table 2 that in the same sample set, the average recognition accuracy of cascade forest classifier is higher than that of BP neural network classification, SVM classifier and RF integrated classifier. With the increase of training samples, the pattern recognition accuracy of cascade forest ensemble classifier increases.

5. Conclusion

In this paper, a method of pattern recognition for partial discharge of transformer based on deep forest algorithm is proposed, which solves the defects that traditional neural networks and support vector machines need to perform human computational features when used, and reduces the training parameters and improves the accuracy of pattern recognition. The experimental results show that the deep forest model has great advantages in the partial discharge pattern recognition of transformer and has a good development prospect in the field of intelligent assessment of transformer insulation.

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