A Convolutional Neural Network-based UHF Partial Discharge Atlas Classification System for GIS

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Abstract. In order to solve the difficult problem of partial discharge pattern recognition caused by large amount of partial discharge detection data and complex multi-source, a partial discharge pattern recognition algorithm based on VGG-16 convolution neural network is proposed. The parameters of VGG-16 network model are optimized in convolution layer, pool layer and connection layer by means of migration learning. The VGG-16 model is superior to LeNet-5 model and has higher recognition accuracy.

Keywords: Gas Insulated Switchgear, Convolution neural network, image recognition, UHF interference

1. Introduction

Gas Insulated Switchgear (GIS) is one of the key equipment of the power grid with SF6 gas as the insulating medium. With the continuous increase of the proportion of GIS in the power grid and the development of partial discharge detection of combined electrical appliances, the following problems exist in GIS UHF partial discharge detection:

- The performance of testing instruments of different manufacturers and models varies greatly, the types and formats of data storage are different, and different forms of unstructured data are exported. Traditional statistical analysis techniques cannot realize the management and application of such data.
- The work of partial discharge detection is relatively complicated. There are a lot of interference signals around the GIS, which leads to misjudgments and missed judgments by the inspectors. The reliability of the detection results largely depends on the professional level of the inspectors, which severely restricts the development of the PD detection of combined electrical appliances and the improvement of equipment condition evaluation ability.

In response to the above problems, a lot of research have done on the classification of partial discharge atlas by domestic and foreign scholars. Wang Yongqiang et al. [2] introduced the Friis transmission equation to construct a quantitative calculation model for partial discharge. Zhuo Ran and Lin Junyi of Chongqing University [3][4] used the characteristics of discharge types to construct feature quantities for various defects and used statistical feature methods to extract features to identify partial discharge types. Tian Yan et al. [5] proposed a feature parameter extraction method based on the texture feature of the time-frequency distribution image. They used S-transformation to transform the partial discharge UHF signal into a frequency distribution image, and then used the gray-level co-occurrence
matrix algorithm to extract texture feature parameters from the time-frequency distribution image. Liu Ronghai et al. [6] used support vector machine machine learning methods and image gray-scale processing methods to achieve intelligent recognition of typical GIS defects.Liu Ronghai et al. [6] used SVM machine learning method and image gray processing method to realize intelligent recognition of GIS typical defects.

In summary, the classification methods of GIS UHF partial discharge atlas can be divided into SVM and convolutional neural networks. It is difficult to implement the SVM method to classify GIS UHF massive partial discharge atlas of different instrument manufacturers, at the same time, the classification of multiple types of defects requires the construction of multiple classifiers, and the training is complicated. In the field inspection, the UHF partial discharge defect map has a certain offset in phase and amplitude compared with the typical map, and the deep convolutional network has the characteristics of invariance to the translation, scaling and distortion of the input sample [7]. This paper uses deep convolutional network (CNN) to classify UHF atlas of different manufacturers.

2. Establishment of UHF pd atlas library

By combing through the partial discharge detection atlas data of the substation of a power supply company in a certain area, an atlas library is established, including the discharge type, the detection atlas, and the corresponding discharge type under different atlas.

UHF atlas are generally used in the form of PRPD and PRPS:

- The PRPD diagram is also called pulse phase diagram, which focuses on recording the relationship between the intensity, frequency and phase of the discharge signal in a certain period of time. Generally the PRPD diagram uses a two-dimensional display method.

- The PRPS diagram is also called the pulse sequence phase diagram, which focuses on recording the relationship between the discharge signal intensity, phase and the number of power frequency cycles (pulse sequence) within a certain period of time. Generally, the PRPS diagram uses a three-dimensional display method.

Discharge types include tip discharge, insulation discharge, suspension discharge, free metal particles, and interference. Combining technical specifications [8] and on-site testing experience, typical UHF partial interference electrical signals near combined electrical appliances include: mobile phones, lights, radars, engines, and electronic fences.

The typical PRPD and PRPS patterns of each interference are given in the literature [8]. Among the 55 substations under the jurisdiction of State Grid Dongying Power Supply Company, 48 are GIS-structured substations, using partial discharge inspection instruments and oscilloscopes to collect PRPD and PRPS atlas of UHF partial discharge interference signals in 48 substations. The measuring point for the interference signal collection is the basin insulator on the GIS for measurement. The measuring point is selected as shown in Figure 1.

![Fig. 1. The selection of measuring points](image)

Around the GIS, an oscilloscope is used to capture the interference waveform, analyze the characteristics of the interference signal, and perform manual matching with various interference signals to determine the source of the interference signal. Use the partial discharge inspection instrument to
measure at the same time, the PRPD and PRPS atlas are obtained to establish the interference signal atlas library.

Fig. 2. The on-site sensor placement

Field tests found that three types of interference signals generally exist in a substation in Dongying, namely cell phone interference, indoor fan interference, and electronic fence interference.

Fig. 3. The mobile phone interference signal

Fig. 4. The fan interference signal

Fig. 5. The electronic fence interference signal

3. CNN-based partial discharge pattern recognition algorithm

3.1. Convolutional neural network structure

Convolutional neural network is a supervised deep learning classification model that can identify key features from the sample atlas[14]. CNN network structure includes input layer, convolutional layer, pooling layer, fully connected layer and SoftMax output layer. Its structure is shown in Figure 6, where the convolutional layer performs convolution calculation on the image to extract multiple features, and uses the pooling layer to subsample the feature map. The calculation formula of the convolutional layer is:

\[ y = f \left( \sum_{j=0}^{I-1} \sum_{i=0}^{J-1} x_{m+i,n+j} \omega_{ij} + b \right) \]  

(1)

\( x \) is the two-dimensional vector of \((M, N)\) in the image, \( w \) is the convolution kernel with length and width of \( j \) and \( i \) respectively, \( b \) is the bias term. \( y \) is the result of convolution calculation, \( f() \) is the activation function.
Pooling layer calculation methods include average pooling, maximum pooling, overlapping pooling, Gaussian pooling and random pooling.

Through the multi-layer combination of convolutional layer and pooling layer, the dimensionality of image features is reduced. Finally, the feature sub-map is integrated through the full connection, and the classifier is used for classification.

![Fig. 6. The Structure of multi-layer convolutional network](image)

### 3.2. CNN training

The convolutional neural network uses the activation function to take the output of the previous layer as the input of the next layer through feedforward calculation, and the final network output is expressed as:

\[
O = f_n(...f_2(f_1(XW_1)W_2)...W_n)
\]

(2)

Among them, \(f()\) is the activation function, \(X\) is the input data, and \(W\) is the parameters of each layer. Each layer parameter \(W\) in the network model includes weights and biases, and uses gradient descent method to update and optimize network parameters to minimize errors.

### 3.3. Partial discharge pattern recognition method based on VGG-16

This paper uses a typical convolutional neural network VGG-16 structure to realize the recognition of partial discharge image patterns. The VGG-16 convolutional neural network contains 16 weight layers, which are 13 convolutional layers and 3 fully connected layers. In this paper, five atlas classification labels are used as the SoftMax classifier in the VGG-16 network, and the activation function of the model adopts the ReLU function.

The VGG-16 network is trained in the ImageNet database and has strong deep feature learning capabilities. It has a large number of trained parameters and weights [15]. To avoid training the entire network from scratch, reduce network training time and improve network training efficiency. In this paper, the trained VGG-16 network is used as the pre-training model of this model, and the pre-trained model parameters are "transferred" to this research model by fine-tuning the transfer learning method. This paper also uses the parameters of the pre-trained model to optimize the model parameters of the convolutional layer, the pooling layer and the fully connected layer to solve the problem of the classification of UHF detection atlas and the recognition of partial discharges. The specific implementation process is:

- A certain proportion of UHF atlas is randomly selected from the sample library as the training sample set input model.
- Perform image segmentation and linear normalization processing on the training sample image data to standardize the size and resolution of the image.
- Based on the VGG-16 model, the graph pattern recognition model is constructed, and the parameters of 13 convolutional layers and pooling layers are initialized by transfer learning.
- Use the training sample set to learn and train the constructed neural network, and use the iterative cross-entropy cost function to optimize the parameters of each layer.
- Normalize the test sample data, input the trained model, and output the pattern recognition dismissal to verify the accuracy of the model.

The specific identification process is shown in the Figure 7.
5. Categories of training sample sets  

5. Categories of test sample sets  

Image preprocessing  

Graph recognition model  

Transfer learning  

VGG-16 network model  

Convolutional layer  

Pooling layer  

Fully connected layer  

Classifier  

5-label SoftMax classifier  

Output pattern recognition results  

Fig. 7. The atlas pattern recognition process

4. Results and analysis of recognition

This paper uses the TensorFlow deep learning framework and Python language to build a network model based on the VGG-16 convolutional neural network structure, utilizes the UHF atlas obtained by the live detection and inputs the model for training and recognition. The recognized categories include tip discharge, insulation discharge, suspension discharge, free metal particles and interference.

Fig. 8. The atlas training

For the 500 sample data sets obtained, they are divided into 400 training sets and 100 test sets, with 300 iterations. Use the model in this paper to perform pattern recognition on sample data.

In the VGG-16 convolutional neural network structure, the input layer is preprocessed 512*512 data, and the convolution layer uses a 3*3 convolution kernel with a step size of 1. The pooling layer uses a 2*2 pooling window with a step size of 2. The output uses SoftMax classifier, and the model's activation function uses ReLU function. After 300 iterations, the accuracy rate of the recognition results of the training data has reached 100%. Then 300 pieces of test data are input into the model, the average accuracy rate of the algorithm on the 5 categories of recognition is 95.1%.

Literature [7] has compared and analyzed the proposed LeNet-5 structure of the neural network in the recognition of partial discharge patterns correctly better than the support vector machine and BP neural network algorithm. Therefore, this paper only compares the recognition effect of the LeNet-5 structure and the VGG-16 structure. For 500 data samples obtained by live detection, the recognition effects of different models are shown in Table 1. Compared with LeNet-5, the VGG-16 model has additional convolution and pooling layers, which can extract more subtle features in the map, so the
VGG-16 model is better than the LeNet-5 model, and the test results also further verify that the VGG-16 model has a higher recognition accuracy.

**Table 1. Test results of different models**

| Type of discharge          | recognition accuracy % |
|----------------------------|------------------------|
|                            | LeNet-5                | VGG-16NET              |
| Tip discharge              | 93.2                   | 95                     |
| Insulation discharge       | 90                     | 92                     |
| Suspension discharge       | 95.1                   | 96.61                  |
| Free metal particles       | 89                     | 94                     |
| Interference               | 95.8                   | 97.8                   |
| Average recognition accuracy % | 92.62                | 95.1                   |

5. Conclusion

This paper proposes a convolutional neural network based on the VGG-16 structure under complex multi-source data to identify different types of UHF maps, and apply it to actual operation and maintenance. A GIS UHF partial discharge jamming signal recognition system is proposed for real-time analysis of on-site detection background algorithms. The system was applied to the substation site, and successfully found the interference signal problem existing in the substation site, which improved the efficiency of operation and maintenance. With the increase of live detection data and cases, deep learning can be used to analyze UHF partial discharge atlas data and the causes of defects, continuously optimize the recognition algorithm, and improve the accuracy of online recognition.

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