GIS Partial Discharge Patterns Recognition with Spherical Convolutional Neural Network

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Abstract. The ubiquitous construction of the power Internet of Things provides a new idea for the real-time and accurate diagnosis of GIS partial discharge online monitoring fault diagnosis. However, the traditional partial discharge fault diagnosis method is difficult to solve the problem that the fault information of different online monitoring systems is different from the reference axis. In order to solve the problem that the fault information is difficult to identify in rotation and transformation, and improve the accuracy of fault diagnosis, this paper proposes a spherical convolutional neural network based on complex data sources. First, the PRPS picture transmitted to the ubiquitous power Internet of Things terminal is selected as the fault feature information. Secondly, a generalized Fourier algorithm (GFT) algorithm is used to construct a spherical convolution structure for PD pattern recognition. The algorithm can perform automatic feature extraction. Thirdly, the spherical convolutional neural network-based PD recognition method is applied to processing of the complex data sources with 84.88% average accuracy rate. It shows that the PRPS 3D map is one of effective way to avoid the complexity of artificial feature extraction for spherical CNN and in the meantime, it can also improve the accuracy of fault diagnosis.

1. Introduction

Gas-insulated combination electrical appliances are widely used as protection and control devices in power system power systems due to their high reliability, small footprint, and maintenance-free. However, there is a risk of failure in the actual running GIS, and the failure rate presents a 'potted' curve with the running time [1-2]. Once the GIS fails, it will cause an inevitable blackout and seriously threaten the safe operation of the power system. Therefore, online monitoring of power equipment to detect faults during the incubation period and effective maintenance is of great significance for ensuring the safety and reliability of the power grid.

GIS faults are mostly insulation faults, while insulation faults are manifested in the form of partial discharges. At the same time, the appearance of partial discharge will further aggravate insulation aging [3]. Fault detection is performed by detecting electromagnetic, acoustic, and optical phenomena excited by partial discharge. At present, the main detection methods are pulse current method, ultra-
high frequency method, ultrasonic method, optical fiber detection method and chemical product decomposition method [4]. Among them, the UHF method is widely used due to its strong anti-interference and high detection sensitivity.

In view of GIS partial discharge pattern recognition, feature extraction is used to extract features of partial discharge UHF signals, and then machine learning methods are used for pattern recognition classification. At present, the main researches on the characteristic parameters of GIS partial discharge are mostly concentrated on the Weibull distribution parameter, time-resolved partial discharge (TRPD), Phase Resolved Pulse Sequence (PRPS) and phase-resolved partial discharge (TRPD) [5-7]. The principal component analysis, self-encoder and other methods are used to carry out feature dimension reduction and extract key feature parameters. The current main methods for pattern recognition classification are support vector machines, decision trees, neural networks, and their various improvements [8-10].

With the development of deep learning, Jiang Xiuchen et al. proposed a pattern recognition of partial discharge PRPS patterns using deep convolutional neural networks, which effectively weakened the interference of artificial feature engineering and accelerated the model's accuracy while improving the model's accuracy [11]. Identify the rate. Li Gaoyang et al. used multi-resolution convolutional neural networks combined with cyclic neural networks for pattern classification, which effectively improved the accuracy of the model [12]. However, convolutional neural networks cannot achieve recognition of rotated images. Under the background of ubiquitous power Internet of Things, because the fault data of different online monitoring systems is different, the device information represented by it is equivalent to the problem of multi-angle option.

In order to solve the problem that the image data representing the fault information under the ubiquitous power internet of things is invalid due to the flipping property, another deep convolution spherical neural network is proposed. While solving the data restaurant problem, it satisfies the real-time diagnosis and processing of big data under the ubiquitous power Internet of Things. In this paper, we use the spherical convolutional neural network as the pattern recognition classifier as well as use the PRPD three-dimensional model of the complex data source combined with the experiment and field as an input to train a general GIS partial discharge fault diagnostic tool. The rest of the paper is structured as follows. We shall first briefly introduce the spherical CNN in Section 2. The details of the spherical CNN model and the comprehensive framework used are discussed in Section 3. In the next section, the complex data of GIS is applied to test the classification accuracy. Finally, some conclusions are drawn in Section 5.

2. Spherical Convolutional Neural Network

Convolutional neural network is named for its unique convolutional calculations. With the sparse interactions, parameter sharing, and equivariant representations, it can to a large degree improve the efficiency of the system. Analogous to the translational invariance of traditional convolutional neural networks in 2D space, the spherical convolutional neural network has the characteristics of rotational symmetry in three-dimensional space to ensure the generalization performance of the system for 3D signals. A spherical CNN architecture is formed with convolutional layers, pooling layers, and full-connected layers [13]. The spherical convolution is calculated by taking inner product between a spherical signal and rotated spherical filter [14-15].

A detailed description of the characteristics of a spherical CNN is as follows: (1) Sparse interactions. The size of the convolution kernel is much smaller than the size of the input, which illustriously enhances the efficiency of the network. The cells in the deep layer of the network interact indirectly with most of the inputs. (2) Parameter sharing. In a spherical CNN, each element of the kernel acts on each location of the input. Therefore, convolution greatly outperforms the multiplication of dense matrices in terms of storage requirements and statistical efficiency. (3) Rotational symmetry. For spherical convolution, the special form of parameter sharing leads to rotational symmetry of the neural network layer. Thus the output signal changes with the same properties as the input signal.
3. Proposed method

3.1. Signal Preprocessing
Since the fault data set is composed of the field data and the experimental data, it is considered that the field data comes from different voltage levels and different manufacturers' equipment, and there are omissions, negligence and other problems in the data accumulation process, resulting in data missing, repeated and the format and size of unstructured data are not uniform. Therefore, it is necessary to use data cleaning to discover the most realistic law between fault signals and then identify fault types.

The field fault data is derived from the different voltage levels and equipment of different equipment manufacturers, resulting in different fault data sets, physical meanings, and so on. At the same time, different acquisition devices will also cause unstructured data to have different formats and sizes. Therefore, the fault set needs to be normalized to solve the same problem of the Subsequent spherical convolutional neural network input, and improve the generalization ability of the model to the field data. Using the moment-based image normalization technique [16], the basic working principle is as follows: Firstly, the parameters of the transformation function are determined by using the moments in the image which are invariant to the affine transformation, and then the original image is transformed by the transformation function determined by this parameter. Is a standard form of image (this image is independent of affine transformation). In general, the moment-based image normalization process consists of four steps: coordinate centering, x-shearing normalization, scaling normalization, and rotation normalization. The calculation formula is defined as:

\[
y = \frac{x - \text{MinValue}}{\text{MaxValue} - \text{MinValue}} \quad (1)
\]

Where \(x\) and \(y\) are the values before and after the conversion, and \(\text{MaxValue}\) and \(\text{MinValue}\) are the maximum and minimum values of the sample, respectively.

3.2. Fast Spherical Convolution with GFT
Analogous to planar convolution, spherical convolution is defined as the same as Taco S. Cohen’s that the inner product between a spherical signal and rotated spherical filter. Square up the signal \(f\) and filter \(\Psi\) is vector-valued functions on the sphere. The \(S^2\) convolution is defined as:

\[
f \ast \Psi(R) = \int_{S^2} \sum_{k=0}^{K} f_k(x) \Psi_k(x) (R^{-1}x) dx \quad (2)
\]

where the \(f: S^2\) for \(K\) channels.

It is worth noting that the result of the convolution calculation in (1) is the function on the rotation group \(SO(3)\) not on the sphere \(S^2\). It is necessary to define the convolution calculation on \(SO(3)\) as:

\[
f \ast \Psi(R) = \int_{SO(3)} \sum_{k=0}^{K} f_k(R') \Psi_k(x) (R^{-1}R') dR' \quad (3)
\]

Analogy to planar convolution can be quickly calculated by Fast Fourier transform(FFT). For spherical convolution, there are corresponding generalized Fourier algorithm(GFT) and fast generalized Fourier algorithm(FGFT) on the rotating group. The GFT is defined as:

\[
\hat{f}^l = \int f(x) U^l(x) dx \quad (4)
\]

where \(X\) signify \(S^2\) or \(SO(3)\). For \(S^2\), there is the spherical harmonics \(Y^l_m(x)\) indexed by \(l \geq 0\) and \(-l \leq m \leq 1\). For \(SO(3)\) ,there are the Wigner D-functions \(D^l_{mn}(R)\) indexed by \(l \geq 0\) and \(-l \leq m, n \leq l\). The inverse \(SO(3)\) is defined as:

\[
f(R) = \sum_{l=0}^{l} (2l + 1) \sum_{m,n=-l}^{l} \hat{f}^l_{mn}(R) \quad (5)
\]
and similarly for $S^2$. The spherical convolution in the spectrum is shown in Fig. 1.

![Figure 1. Spherical convolution in the spectrum.](image)

The input signals $f$ and the filter $\psi$ are FFT, tensored, summed over input channels. $\alpha, \beta$ are the parameters of sphere. $\alpha, \beta, \gamma$ are the parameters of $SO(3)$.

4. Experiments

4.1. Data Acquisition

Taking into account the actual situation of the data under the ubiquitous power Internet of Things, the method of using laboratory data for flipping and transformation is used to construct complex partial discharge data to ubiquitous complex data sources under the power Internet of Things. Studies have shown that the partial discharge of the protruding defect under the lightning impulse voltage is much higher than the protruding defect under the power frequency. Therefore, the simulated GIS is subjected to lightning impulse and power frequency withstand voltage tests in the laboratory to obtain a rich discharge sample.

The GIS simulation model in the laboratory and the main insulation defects inside the GIS is shown in Figure 2. The UHF sensor detection frequency band is 300MHz-2000MHz, and is composed of an amplifier, a high-pass filter, a detector and a shielding case. The working bandwidth of the amplifier is 300MHz-1500MHz, and the gain is 40dB.

![Figure 2. The GIS simulation model in the laboratory and the main insulation defects inside the GIS](image)
power internet of things. For 1200 sets of data, 800 sets were selected as training data, and the remaining 400 sets constitute test data.

4.2. Result and Discussion
For this experiment testing set, BPMM model, SVM model, 2D DCNN model and spherical CNN model are used to train and identify PD sources. The recognition results are shown in Table 1.

| Category          | Spherical CNN(%) | DCNN(%) | SVM(%) | BPNN(%) |
|-------------------|------------------|---------|--------|---------|
| Protrusion discharge | 92.25            | 62.25   | 89.75  | 85.25   |
| Particle discharge | 91.75            | 60.50   | 90.25  | 85.5    |
| Void discharge    | 83.75            | 58.75   | 77.75  | 68.25   |
| Surface discharge | 71.75            | 56.25   | 73.50  | 56.25   |
| Overall           | 84.88            | 59.44   | 82.82  | 73.81   |

As shown in Table 1, the average accuracy of the spherical CNN is 84.88%. The accuracy of the void discharge and the surface discharge are relatively low. The spherical CNN performs competitively with the state of the art results compared to other methods. The surface defects of the insulator are significantly more sensitive to lightning impulse voltage and overvoltage than the power frequency withstand voltage. However, studies have shown that there is almost no sign of the flash of the insulator. This defect recognition rate is relatively low due to the current detection method is difficult to detect the sign signal. Insulator internal defects mainly refer to small voids in the mold resin or voids in the layered region between the insulating material and the metal insert. With the accumulation of electric fields for a long time, the instability of partial discharge under such defects leads to low recognition accuracy.

The average recognition accuracy of SVM, DCNN and BPNN methods is 82.82%, 59.44% and 73.81%. Under the premise of the application of ubiquitous power Internet of Things, the spherical convolutional neural network significantly improves the accuracy of information fault recognition after the rotation and symmetric transformation of the partial discharge map. However, there is still a need to further improve the network layer parameters to further improve the accuracy of fault identification.

5. Conclusion
In the work reported in this paper, we have developed a novel deep learning architecture for UHF signal source recognition, a spherical CNN after GFT representation, which has the ability of feature extraction and diagnosis within the same architecture. Spherical CNN based pattern recognition is more accurate for for the partial data of the partial discharge map under the ubiquitous power Internet of Things compared with the DCNN, BPNN and SVM methods. The conclusions can be drawn as follows:

• Spherical CNN has improved accuracy by 3.55%, 18.25% and 27% compared with DCNN, SVM and BPNN methods. As the data set expands and the number of network layers deepens, the recognition accuracy of the model will further increase.

• Under the application of the power Internet of Things platform, the convolutional neural network can solve the problem that the data collected by different online monitoring devices are not uniform in the coordinate axes. Therefore, it is more suitable for engineering applications under the power of the Internet of Things.

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