SVM-based Partial Discharge Pattern Classification for GIS

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Abstract. Partial discharges (PD) occur when there are localized dielectric breakdowns in small regions of gas insulated substations (GIS). It is of high importance to recognize the PD patterns, through which we can diagnose the defects caused by different sources so that predictive maintenance can be conducted to prevent from unplanned power outage. In this paper, we propose an approach to perform partial discharge pattern classification. It first recovers the PRPD matrices from the PRPD2D images; then statistical features are extracted from the recovered PRPD matrix and fed into SVM for classification. Experiments conducted on a dataset containing thousands of images demonstrates the high effectiveness of the method.

1. Introduction
Gas insulated substation (GIS) is extensively used in electrical industry [1] due to its compactness and insensitivity to environment. To ensure the safety of electric power systems, predictive maintenance of GIS is routinely performed by experienced personnel. They measure partial discharges (PD), which are localized dielectric breakdowns in small regions of insulating systems [2], to diagnose the condition of GIS. The partial discharge patterns can reveal the defects caused by different sources.

Traditional PD pattern classification was conducted manually by experts. With the increase of sensing data, it becomes more and more desirable to make classification and diagnosis automatic. For this purpose, a bunch of methods have been developed [3-7]. For instance, James and Phung calculated the IEC-270 integrated quantities, statistical moments and other fingerprints to recognize the PD patterns within the power frequency cycle [4]. Gao et al. investigated frequency characteristics of PD for classification [6]. As summarized in [7], the common framework shared in most of the methods is composed of two stages, which are feature extraction and pattern classification. Besides these two stages, there is another problem we need to face. That is, the partial discharges collected by PD sensors are stored in the form of graph. The corresponding raw data is unavailable due to the lack of standard protocols from manufacturers.

This paper proposes an approach to classify the PD patterns captured by a PD-Detector. Our method first parse the raw information from PD graphs via image processing techniques. Then, statistical features are calculated and fed into a support vector machine (SVM) [8] for classification. Our approach is validated in a dataset containing thousands of PD graphs and demonstrates promising results.
2. The proposed method

There are two ways to perform PD pattern classification. One is extracting features from PD graphs directly, and the other recovers raw information first and then extract features. Our approach takes the latter way. In this paper, we first design an approach to parse raw data from PD graphs collected by a PD-Detector. Then, we extract statistical features from the recovered information and use SVM for classification. Each step is introduced in the following subsections.

2.1. Graph parsing

A PD-Detector gathers the phase-resolved partial discharge (PRPD) spectrum. The PRPD spectrum consists of three-dimensional discharge patterns \((\phi, q, n)\), in which \(\phi\) stands for the phase angle, \(q\) is the discharge magnitude and \(n\) is the discharge rate [7]. The patterns are stored in either 2D or 3D forms as shown in Figure 1 (a). Graph parsing in this work aims to recover the raw PRPD matrix when a PRPD2D image is given.

![Figure 1. An example of the partial discharge graph. (a) is PRPD2D and PRPS-3D images; (b) is edge detection result; (c) is Hough transform result; (d) is the visualization of the recovered PRPD matrix.](image)

To this end, we design a parsing procedure based on some image processing techniques. The procedure consists of a couple of steps as presented in Figure 2.

![Figure 2. The procedure of graph parsing.](image)

2.1.1 Extract coordinate axes and axes’ corners. When a PRPD2D image is input, we first filter out the blue phase line and convert the remaining color image into gray level. Then, the Canny operator is applied to detect edges, by which we obtain the edge detection result as shown in Figure 1(b). Based on this, Hough transform is performed to extract the horizontal axis \((\phi)\), the vertical axis \((q)\) and grid lines, as presented in Figure 1(c). Finally, the bottom-left corner \((bl, bl)\) and top-right corner \((tr, tr)\) of axes are determined.
2.1.2 Determine the value \((\phi, q, n)\) for each point. Based on the axes’ corners detected in the previous step, we can estimate the size of each bin on both the phase and the magnitude axis according to the following equations:

\[
\begin{align*}
X_{bin} &= \frac{(tr_x - bl_x)}{72} \\
Y_{bin} &= \frac{(tr_y - bl_y)}{100}
\end{align*}
\]

where the discharge magnitude axis Y is divided into 100 bins and the phase axis X is divided into 72 bins, each of which stands for 5°.

Once the scale of axes is determined, we recover the PRPD matrix. We first initialize a 2D matrix of size \(100 \times 72\) and all entries are set to 0. Each entry \((i, j)\) corresponds a grid \((x, y)\) on the PRPD2D image, in which the grid \((x, y)\) is estimated by

\[
\begin{align*}
x &= \text{round} \left( bl_x + i \cdot X_{bin} - 0.5 \cdot X_{bin} \right) \\
y &= \text{round} \left( bl_y + j \cdot Y_{bin} + 0.5 \cdot Y_{bin} \right)
\end{align*}
\]

The RGB value of each grid on the PRPD2D image represents the discharge rate. According to the color table which is prior constructed, we can roughly get the discharge rate and therefore reconstruct the PRPD matrix. Figure 1(d) visualizes the recovered PRPD matrix, which validated the effectiveness of our graph parsing method.

2.2. Feature extraction

In this work, the features used for PRPD pattern classification is extracted from the reconstructed PRPD matrix. 18 statistical features are extracted in total. They are skewness, kurtosis, cross correlation factor (cc) and asymmetry calculated from three distributions \(q_s \sim \phi\), \(q_m \sim \phi\), and \(n \sim \phi\), in which \(q_s \sim \phi\) refers to the distribution of the average discharge magnitude with respect to the phase angle, \(q_m \sim \phi\) is the distribution of the maximum discharge magnitude w.r.t the phase angle, and \(n \sim \phi\) is the distribution of the discharge rate and the phase. The procedure of feature extraction is introduced in the following:

| Algorithm 1. Feature extraction |
|-------------------------------|
| 1. Calculate the three distributions from the PRPD matrix; |
| 2. Separate each distribution into two parts, one is of positive phase and the other has negative phase; |
| 3. Calculate the mean \(\mu\) and the standard deviation \(\sigma\) for both positive and negative parts of all distributions; |
| 4. Calculate the skewness and kurtosis for each part of three distributions, by which we obtain 12 features in total; |
| 5. Calculate the cross correlation factor and asymmetry for each distribution, by which we get 6 features in total. |

The above mentioned features are widely used in PRPD classification. For the purpose of self-containedness, we briefly introduce them as follows.

2.2.1. Skewness. The skewness feature measures the degree of tilting of a distribution with respect to normal distribution. It is defined by
Here, $x_i$ is the $i$-th phase and $f(x_i)$ is the probability at $x_i$. $N$ is the number of phase bins in half cycle (either positive or negative).

### 2.2.2. Kurtosis
Kurtosis measures the peakness of a distribution. It is defined as

$$K = \frac{\sum_{i=1}^{N} (x_i - \mu)^4 \cdot f(x_i)}{\sigma^4 \sum_{i=1}^{N} f(x_i)} - 3$$

When $K = 0$, it indicates that the distribution has the same sharpness as a normal distribution. If $K < 0$, it is flatter; otherwise, it is sharper.

### 2.2.3. Cross correlation factor (CC)
CC measures the similarity between the positive half cycle and the negative half cycle of a distribution. It is defined by

$$CC = \frac{\sum_{i=1}^{N} x_i^+ x_i^- - \frac{N}{N^+} \sum_{i=1}^{N} x_i^+ \sum_{i=1}^{N} x_i^-}{\sqrt{\left[\sum_{i=1}^{N} (x_i^+)^2 - \frac{N}{N^+} \sum_{i=1}^{N} x_i^+ \sum_{i=1}^{N} x_i^+ / N\right]} \sqrt{\left[\sum_{i=1}^{N} (x_i^-)^2 - \frac{N}{N^-} \sum_{i=1}^{N} x_i^- \sum_{i=1}^{N} x_i^- / N\right]}}$$

When CC equals 1, it indicates that the two halves are highly similar; otherwise, they are not.

### 2.2.4. Asymmetry
Discharge asymmetry measures the difference of discharge level between positive and negative half cycles. It is

$$Q = \frac{Q^+ / N^+}{Q^- / N^-}$$

in which $Q^+$ and $Q^-$ are, respectively, the sum of discharges of a distribution in the positive and negative half cycles. $N^+$ and $N^-$ are the number of discharges in the corresponding half cycles. When $Q = 1$, it indicates equal discharge levels.

### 2.3. PD pattern classification
When electrical insulations work normally, there should be no discharge detected. Otherwise, PD detectors will capture partial discharges. According to the sources that lead to defects, we can categorize the PD patterns into four major classes: 1) corona discharge, which is an electrical discharge brought on by air surrounding an electrically charged conductor; 2) surface discharge, which occurs along the surface of solid insulations when the surface tangential electric field is high enough to cause a breakdown; 3) floating electrode partial discharge, which happens when there is an ungrounded conductor within the electric field between conductor and ground; and 4) particle
discharge, which occurs when conductive particles contaminate insulation medium. Typical examples of each category are presented in Figure 3.

![PD Graph Examples](image)

**Figure 3.** Typical examples of PD graph for each category.

In this work, we employ the support vector machine (SVM) [8] for classification. SVM constructs a set of hyperplanes in the high-dimensional feature space that have the largest distances to the nearest training-data point of each class. It is extensively used in supervised machine learning for classification when the dimensionality of features are low. Therefore, SVM fits our task well.

When a set of training data \((x_i, y_i)\) is given, SVM determines the hyperplane \((w, b)\) by minimizing the following objective function:

\[
\min_{w, b} \frac{1}{n} \sum_{i=1}^{n} \zeta_i + \lambda \|w\|^2 \quad \text{s.t.} \quad y_i (w \cdot x_i + b) \geq 1 - \zeta_i \text{ and } \zeta_i \geq 0
\]  

(7)

Here, \(x_i\) is the i-th feature vector, \(y_i\) is the labelled class, and \(\lambda\) is a scaling factor. This function can be optimized via quadratic programming algorithms.

3. Experiments

To validate the proposed method, we build a dataset that contains 4600 PRPD2D images collected by PD-Detectors when performing routinely maintenance. Each category is of 1150 images. In our experiment, we randomly take 60% images for training and the remaining for test.

Table 1 lists the classification accuracy for each class and the mean accuracy reaches to 0.9158. The experiment validates the effectiveness of our proposed method.

| Category  | Corona | Particle | Floating | Surface |
|-----------|--------|----------|----------|---------|
| Accuracy  | 0.9457 | 0.9043   | 0.8804   | 0.9326  |

4. Conclusions

In this paper, we have presented an approach to perform partial discharge pattern classification. Our approach first reconstructs the PRPD matrix from the PRPD2D images collected by PD-Detectors; then 18 statistical features are extracted from the recovered PRPD matrix and fed into SVM for classification. We have validated our approach in a dataset containing 4600 images. Experiments have demonstrated the high effectiveness of the method.
References
[1] Bolin P and Koch H 2005 Introduction and applications of gas insulated substation (gis) Power Engineering Society General Meeting IEEE San Francisco, CA, USA
[2] Aaradhi V and Gaidhani K 2013 Partial discharge in gas insulated substations (gis): effects, mitigation & analysis International Journal of Scientific & Engineering Research 4(3) pp 1-6
[3] Guo Z H, Wang H, Xiu-Ming D U, et al 2016 GIS Partial Discharge Pattern Recognition Based on Dimension Reduction Based on Rough Set Theory 2016 International Conference on Power, Energy Engineering and Management
[4] James R E and Phung B T 1995 Development of computer-based measurements and their application to pd pattern analysis IEEE Trans. Dielectr. Electr. Insul. 2(5) pp 838-856
[5] Fangcheng L, Hu J, Wang Z, et al 2015 GIS Partial Discharge Pattern Recognition Based on Principal Component Analysis and Multiclass Relevance Vector Machine Transactions of China Electrotechnical Society 30(6) pp 225-231
[6] Gao W, Zhao D, Ding D, Yao S, Zhao Y and Liu W 2015 Investigation of frequency characteristics of typical pd and the propagation properties in gis IEEE Trans. Dielectr. Electr. Insul. 22(3) pp 1654-1662
[7] Sahoo N and Salama M 2005 Trends in partial discharge pattern classification: a survey IEEE Trans. Dielectr. Electr. Insul. 12(2) pp 248-264
[8] Chang C and Lin C 2011 Libsvm: a library for support vector machines ACM Transactions on Intelligent Systems and Technology 2(3) pp 1-27