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# Recent Advances and Research in Online Monitoring Pattern Recognition of Cable Partial Discharge Based on Computer Technology

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**Abstract:This article provides a detailed review of recent advancements and significant achievements in the field of cable partial discharge online monitoring pattern recognition. It examines the evolution of monitoring technologies and the integration of advanced data analytics that have contributed to more accurate and reliable identification of partial discharge patterns. The article also addresses the existing challenges in partial discharge pattern recognition, such as the difficulties in distinguishing between various types of discharges under complex operational conditions and the need for more robust algorithms capable of handling large datasets with high noise levels. To overcome these challenges, potential solutions are proposed, including the application of machine learning techniques, the development of enhanced signal processing methods, and the use of more sensitive and precise sensors.Furthermore, the article explores the implications of these advancements for engineering practices, particularly in the context of predictive maintenance and the early detection of faults in cable systems. The integration of these advanced monitoring and pattern recognition systems is expected to lead to significant improvements in the operational efficiency and safety of electrical networks.**

**Keywords:**Partial discharge, online monitoring, pattern recognition, characteristic quantity.

## 1. Introduction

In order for utility companies to achieve self-enforced and regulated performance goals that apply to them, the need for new tools to help determine the health of modern distribution networks has increased. Partial discharge(PD) signal analysis has been considered as a potential diagnostic tool for condition monitoring of high-voltage power stations.

Currently, there are two data modes for analyzing PD signals, phase-resolved partial discharge (PRPD) mode and time-resolved partial discharge (TRPD) mode. Separate use of different types of data patterns may lead to inconsistent or even conflicting recognition results, but there is complementary information between the two data patterns and data fusion can be carried out.[3-5]

With the development of computer technology and mathematical theory, the methods of PD pattern recognition emerge in endlessly. At the end of the 1960s, the CIGRE working group 21.03 published a classic review of PD recognition [4]. This work involves factors that identify, diagnose the origin of PD discharge and identify external disturbances. The 12 typical PD patterns and 4 additional interference patterns describe the discharge distribution in each part of the AC cycle, as well as the varying test voltage and application time. In the 1990s, Krivda proposed a PD [3] automatic identification method, which includes PD pattern measurement, feature extraction, pattern classification and decision-making process. Based on basic feature extraction and database construction, cluster analysis and neural network are applied. In the 21st century, new PD pattern recognition methods continue to develop, including inductive reasoning algorithms [5], neural fuzzy networks [6], fractal image compression [7], genetic optimization [8], support vector machines [9] and knowledge-based System [10].

## 2. Types of Partial Discharge

The various characteristics of the insulating material and the complexity of the insulating structure result in a rather complicated electric field distribution of the cable, which is prone to partial discharge during operation. There are mainly three types of partial discharge involved in cables:

### 2.1. Corona Discharge

Corona discharge is a kind of partial discharge generated when the surrounding gas medium isin the conductor. Since corona discharge is a tip discharge, its waveform is more regular. Generally, when the power frequency is positive half-wave, the discharge is large and the number of discharges is small. When the negative half-wave is small, the discharge is small and the number of discharges is large. Regardless of the positive and negative half-wave discharge pulses, they are almost equal in amplitude and equally spaced. The characteristics of good repeatability of multiple discharges.

### 2.2. Internal Discharge

Due to the different dielectric constants of the medium and the air gap inside the cable, the voltage distribution is different. The air gap always reaches the breakdown field strength first and breaks down. The voltage at which internal discharge occurs is generally low, and the discharge pulse is more symmetrical in the positive and negative cycles of the power frequency. When multiple bubbles discharge at the same time or there is only a large bubble. But when each discharge is only partial area discharge, it is manifested by the larger distribution of the discharge pulse amplitude.

### 2.3. Surface Discharge

The partial discharge that occurs when the air gap is located on one side is a conductor and theother is a medium is a surface discharge. Its discharge principle is similar to that of internal discharge, but the discharge pulse is asymmetric on the positive and negative cycles of the power frequency due to the action of the electrodes. Surface discharge can also cause electrical aging.

## 3. Challenges of Partial Discharge Online Pattern Recognition

Partial discharge pattern recognition, data collection, denoising, partial discharge location and criticality assessment are the keys to the success of partial discharge online monitoring. In actual online situations, two major challenges must be overcome to attempt autonomous PD pattern recognition in cable status monitoring:

(1) The voltage phase reference is difficult to obtain.

(2) Many online systems monitor three-phase components, and the PD produced by them will be affected by the electric field generated by two-phase or three-phase voltage.

## 4. Pattern Recognition of Partial Discharge Signal

"Pattern" refers to determining the concept and scope of a certain type of things, giving quantitative or structural descriptions, comparing and classifying unknown things with patterns, and making substantive judgments. Since partial discharge is closely related to the insulation defects of equipment, the modes of partial discharge caused by different defects are different. When we use a certain method to identify the pattern of the local discharge, we can make a detailed diagnosis of the nature and severity of the partial discharge, and then make a prediction for the insulation pattern recognition and locate the position of the partial discharge. This is the goal of situational discharge pattern recognition.

There are two main methods of pattern recognition: decision theory method (statistical method)and syntactic analysis method (structural method). At present, the method of partial discharge pattern recognition generally uses the decision theory method, that is, by extracting some characteristic quantities, each pattern is divided into a characteristic space for recognition.

The general pattern recognition system is:

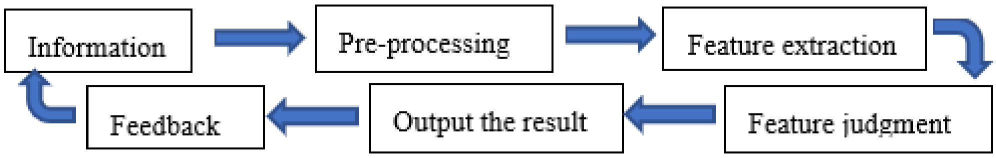


**Figure 1.** The general pattern recognition system

### 4.1. Information Acquisition and Preprocessing

Signal pre-processing, including data denoising [2] [11] [12] is adopted to extract individual PD-like pulses from noisy raw data. The individual pulses are the input of K-Means based PD pattern recognition. It is to be noted that, in addition to PD pulses, this data may contain impulsive noise signals that resemble PD pulses in the time-domain.

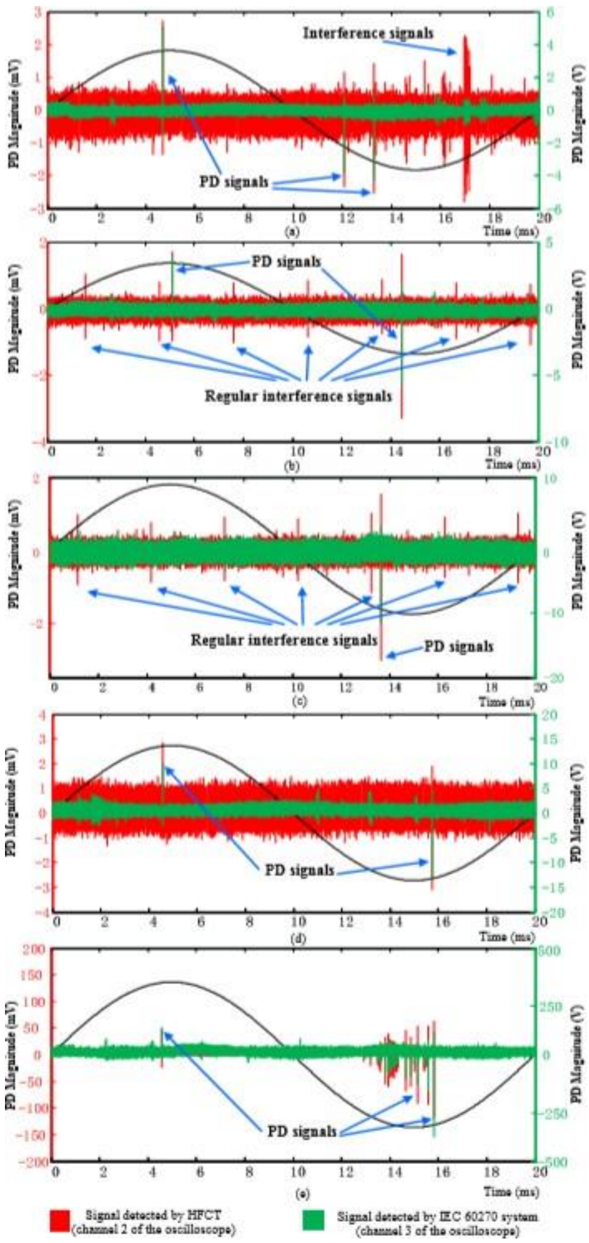

**Figure 2.** PD Transient pulses from HFCT (lower trace) and IEC 60270[17]

## 4.2. Partial Discharge Signal Denoising

Three typical noise and interference signals were detected during the experiments: white noise, regular interference signals and random interference signals.

White noise was detected during PD testing the five types of defect. As shown in Fig. 1, this is a challenge for PD detection. When PD signals have a similar magnitude to the noisy raw data then significant loss of detected PD will occur unless appropriate interference rejection techniques are applied. In addition to the white noise detected in all data sets, other pulsative noise signals were detected. Additionally, random pulsative interference signals were detected during some tests. As some of the regular interference pulses have similar magnitude to PD, if the threshold for PD extraction is set at a level appropriate to the white noise then both PD and regular interference signals will be extracted from raw data.

It is therefore essential to correctly extract PD signals from raw data with white noise, regular interference signal and random interference signal. In the following section the development of an automatic algorithm, capable of processing large volumes of data to separate PD from other signals and to organise the data for recognition systems is outlined.

## 4.3. Pattern Recognition Scheme

### 4.3.1. Back Propagation Neural Network (BPNN)

A three-layered BPNN, which is widely adopted for pattern recognition, is also applied for PD recognition from different sources. BPNN is a multilayer feedforward network that uses error back propagation. The input and output of the network are a nonlinear mapping relationship. BPNN divides data through hyperplane. The neurons in the hidden layer constitute a hyperplane, and one type of neuron corresponds to a hyperplane. The weight between the input layer and the hidden layer determines the slope and position of the hyperplane. The weight between the hidden layer and the output layer determines the logic function. Although the number of nodes in the hidden layer plays an important role in the success of BPNN based pattern recognition, there is no available theory on how the number of nodes in the hidden layer should be chosen [14].

### 4.3.2. SVM

SVM was first proposed by Vapnik in 1995 [7]. The input vectors of SVM are mapped to a high-dimensional space by a non-linear mapping in order to identify an optimal hyperplane which makes the gaps between samples of different classes largest [6, 7]. There are four factors, signal normalisation, kernel function, penalty factor C and kernel function paramount $\gamma$, which significantly affect the accuracy of SVM based pattern recognition [6, 7]. In this work, normalisation is applied to fit the signals into 0 to +1 range; Radial Basis Function (RBF) is chosen as the kernel function, based on references [5], [6] and [7].

### 4.3.3. RS

The flowchart of application of RS theory for development of PD pattern recognition is shown in Figure 3.

Using the training data sets, procedures for attribute reduction and decision rules generation are applied in order to generate initial decision rules.

Thereafter, the decision rules are reviewed to remove isolated rules with low support. Using test data sets, rules validation is applied to assess whether the decision rules generated by training data sets are sufficiently robust. If the accuracy is higher than threshold, the final set of decision rules is generated.

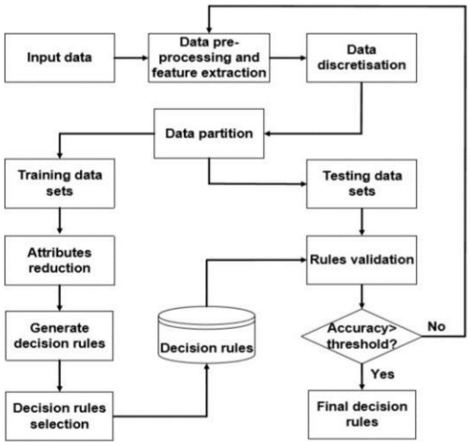

**Figure 3.** Flowchart of RS

### 4.4. K-means

Within the thousands of sets of PD data that the authors have examined, during on-site testing and from on-line monitoring data, PD pulses demonstrate cluster characteristic in the time- domain.

As K-Means is a simple and effective clustering methodology it has been investigated as a tool for identifying PD patterns in the data. The basic flowchart of K-Means based PD pattern recognition is shown in Figure 4.

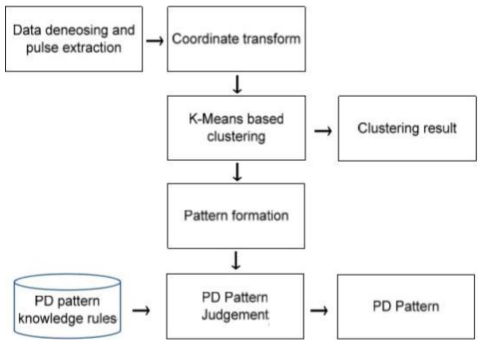

**Figure 4.** Flowchart of K-means

## 5. Problems in the Research and Practice of PD Pattern Recognition

The analysis of literature [4] shows that the classification effect based on wavelet energy information is the best, and the accuracy is higher than that of the entire feature vector. It shows that the shortcoming of support vector machine lies in its robustness to redundant information. Literature [18] proposed a pattern recognition method based on K-means. When corona discharge and internal discharge exist at the same time, the PD pulse needs to be separated in the time domain by other techniques, such as using pulse shape analysis. In addition, further work is needed to develop the ability to distinguish between internal discharge and surface discharge.

A disadvantage of RS is that the method takes more processing time for training and testing than BPNN. The reason for this increasing time for RS is that as the number of sample increases the number of decision rules will also increase. As the testing samples are evaluated with all the decision rules, increasing the number of decision rules increases the time taken. Although both SVM and BP are capable of adaptive generation for large samples and have high signal classification accuracy, the biggest disadvantage of the methods is that they are “Black Box” and do not allow the user to understand the decision making process.

## 6. Conclusion and Discussion

1) The structure of partial discharge patterns is the basis of pattern recognition. The structure of discharge patterns directly affects the extraction of feature quantities and reflects the essential characteristics of different discharge types. The TRPD mode is mostly used to distinguish the discharge sources of different paths in the field; the PRPD mode is widely used in the field.

2) The extraction of feature quantities is the key to partial discharge pattern recognition, and its pros and cons directly affect the classifier's ability to recognize fault patterns.

3) The choice of classifier is also the key to pattern recognition. Optimizing pattern recognition algorithms is the focus of current research.

4) Due to the complexity of partial discharge itself, the uncertainty of fault type classification, and the large number of on-site environmental interference, online partial discharge pattern recognition is still a difficult problem in the current stage of research, and it is urgent for scholars to solve and explore more in depth. problem. Multi-information fusion technology is used to avoid the limitations of a single feature; seeking the best classification decision methodwill become the focus of future research on partial discharge pattern recognition.

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