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Partial discharge pattern recognition of power cable joints using extension method with fractal feature enhancement

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ABSTRACT

This paper proposes a new partial discharge (PD) pattern recognition using the extension method with fractal feature enhancement. First, four common defect types of XLPE power cable joints are established, and a commercial PD detector is used to measure the PD signal by inductive sensor (*L*-sensor). Next, the feature parameters of fractal theory (fractal dimension and lacunarity) are extracted from the 3D PD patterns. Finally, the matter-element models of the PD defect types are built. The PD defect types can be directly identified by the degree of correlation between the tested pattern and the matter-element based on the extension method. The extension method needs representative features to define the interval of the matter-element. In order to enhance the extension performance, we add fractal features that are extracted from the PD 3D patterns. To demonstrate the effectiveness of the extension method with fractal feature enhancement, the identification ability is investigated on 120 sets of field-tested PD patterns of XLPE power cable joints. Compared with the back-propagation neural network (BPNN) method, the results show that the extension method with fractal feature enhancement not only has high recognition accuracy and good tolerance when random noise is added, but that it also provides fast recognition speed.

1. Introduction

Partial discharge (PD) measurement has been widely applied in insulation diagnosis for power equipment. It is an important tool for power apparatus, such as XLPE power cables, power transformers and gas insulation switch (GIS) diagnosis. The main purpose of an insulation diagnosis for power apparatus is to give system operators information on the dielectric deterioration degree of HV equipment (Acir, 2005; Montanari, Cavallini, & Puletti, 2006). Commercial PD detectors are used to measure the electrical signal of electrical or magnetic field variations in a defect model; an experienced expert can use the PD patterns to identify the defect types in the test object. The main parameters of the 3D PD patterns are phase angle φ, discharge magnitude q, and the numbers of discharge n, and they provide the basis parameters for pattern recognition techniques that can identify the different defect types (Satish & Zaengl, 1994).

Fractals have been successfully used in the description of naturally occurring phenomena and complex shapes, such as mountain ranges, clouds, coastlines, and so on, for which traditional mathematical methods were found to be inadequate (Friesen & Mikula, 1987). PD also is a natural phenomenon occurring in electrical insulation systems, which invariably contain tiny defects and non-uniformities and give rise to a variety of surfaces and complex shapes in 3D PD patterns. The complex nature of PD pattern shapes and the ability of fractal geometry to model complex shapes were why the authors were encouraged to study its feasibility for PD pattern interpretation (Jian, Caixin, & Grzybowski, 2008; Lanca, Marat-Mendes, & Dissado, 2001).

Various pattern recognition techniques, including the fuzzy clustering recognition method (Abdel-Galil, Sharkawy, Salama, & Bartnikas, 2005; Abdulhamit, 2006) and the neural network (NN) recognition method, have been extensively used in PD pattern recognition (Candela, Mirelli, & Schifani, 2000; Karthikeyan, Gopal, & Venkatesh, 2008; Karthikeyan, Gopal, & Vimala, 2005; Kuo, 2009). The main advantage of NN is that it can directly acquire experience from the training data. However, the training data must be sufficient to describe a status. Another limitation of the NN approach is the inability to use linguistics to describe the output, because of its difficulty in understanding the content of the network. To overcome the limitations of the NN approach, a new PD recognition method using extension theory has been proposed in

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this paper for classifying PD defect models. The extension theory was first proposed in 1983 by Cai Wen to solve contradictions and incompatibility problems (Cai, 1983). The extension theory consists of the matter-element model and the extended set theory, and it does not require artificial parameters or particular learning processes. To demonstrate the effectiveness of the extension recognition method with fractal feature enhancement, 120 sets of XLPE power cable joint PD patterns were tested. The results showed that the proposed method was suitable for pattern recognition.

2. Outline of extension theory

Extension theory contains the concepts of matter-elements and extension sets and its main application is in solving contradiction and incompatibility problems. The matter-element can easily represent the nature of matter, and the extension set is the quantitative tool of the extension theory which represents the correlation degree of the matter-element by the designed correlation function. Some definitions of extension theory are introduced below (Cai, 1983).

2.1. Matter-element theory

In extension theory, a matter-element uses an equation for describing things as

$$R = (T, c, v), \tag{1}$$

where T represents the matter; c represents the characteristics; and v represents the value of the characteristics, c. If we assume that $C = (c_1, c_2, \ldots, c_n)$ is a characteristics vector, and that $V = v_1, v_2, \ldots, v_n$ is a value vector of C, then the multidimensional matter-element can be defined as:

$$R = (T, C, V) = \begin{bmatrix} T & c_1 & v_1 \\ & c_1 & v_2 \\ & \vdots & \vdots \\ & c_n & v_n \end{bmatrix}, \tag{2}$$

where $R = (T, c_i, v_i)$ $i = 1, 2, \ldots, n$ is defined as the sub-matter-element of R. For example, tennis ball-A has a weight 60 g and a diameter of 6.5 cm. We can describe tennis ball-A by using the matter-element as

$$R = \begin{bmatrix} tennisball-A & weight & 60\text{ g} \\ & diameter & 6.5\text{ cm} \end{bmatrix}. \tag{3}$$

Using the matter-element, we can describe the quality and quantity for a matter, which is a new concept theory as compared with conventional mathematics.

2.2. Extension set

Set theory is a mathematical scheme that describes the classification of an object. The membership function of the traditional fuzzy set describes the value of matter at interval $[0, 1]$. The extension set extends the fuzzy set from $[0, 1]$ to $[-\infty, \infty]$. As a result, it allows us to define a set that includes any data in the domain. An extension set is composed of two definitions as follows (Cai, 1983):

Definition 1. Let U be a space of objects and x an element of U, then extension set $\widetilde{E}$ in U is defined as

$$\widetilde{E} = \{(x, y) | x \in U, y = K(x) \in (-\infty, \infty)\}, \tag{4}$$

where $y = k(x)$ is the correlation function for extension set $\widetilde{E}$. $K(x)$ describes the level between the interval $[-\infty, \infty]$ for each element. An extension set $\widetilde{E}$ in U can be denoted by

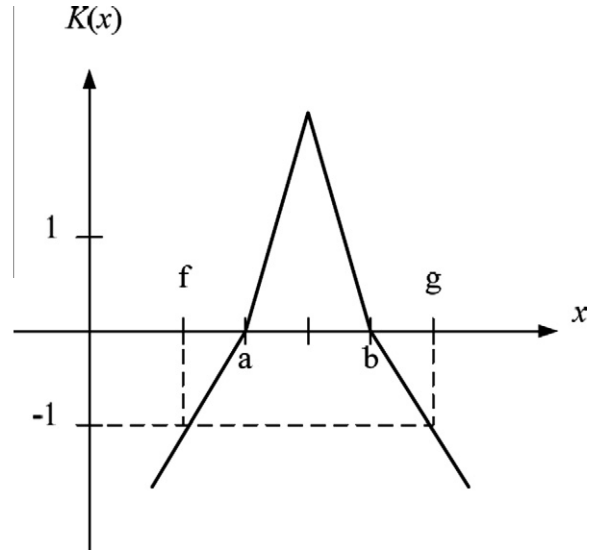

Fig. 1. Extension membership function.

$$\widetilde{E} = E^+ \cup Z_0 \cup E^-, \tag{5}$$

where

$$E^+ = \{(x, y) | x \in U, y = K(x) > 0\}, \tag{6}$$

$$E^- = \{(x, y) | x \in U, y = K(x) < 0\}, \tag{7}$$

$$Z_0 = \{(x, y) | x \in U, y = K(x) = 0\}. \tag{8}$$

E^+ represents the positive field $y = k(x) > 0$, E^- represents the negative field $y = k(x) < 0$, and Z_0 represents the zero boundary $y = k(x) = 0$.

Definition 2. If $X_0 = [a, b]$ and $X = [f, g]$ are two intervals in the real number field, and $X_0 \subset X$, where X_0 and X are the classical and neighborhood domains, respectively, then the correlation function in the extension theory can be defined as (Cai, 1983):

$$K(x) = \begin{cases} \frac{-2\rho(x, X_0)}{b-a}, & x \in X_o \\ \frac{\rho(x, X_0)}{\rho(x, X) - \rho(x, X_0)} & x \notin X_0 \end{cases},$$

where

$$\rho(x, X_0) = \left| x - \frac{a+b}{2} \right| - \frac{b-a}{2} \tag{10}$$

$$\rho(x, X) = \left| x - \frac{f+g}{2} \right| - \frac{g-f}{2}. \tag{11}$$

The correlation function can be used to calculate the membership grade between input x and classical domain X_0. The extension correlation function concept is shown in Fig. 1. When $y = k(x) > 0$, it means x in the interval $[a, b]$. When $y = k(x) < 0$, it means x does not belong to X_0. When $-1 < K(x) < 0$, it is called the extension domain, which means that the element still has a chance of becoming part of the set if conditions change.

3. Extraction of PD features

Fractals have been successfully used to address the problem of modeling and to provide a description of naturally occurring phenomena and complex shapes, for which conventional and existing mathematical methods were found to be inadequate. This technique has increased interest in the classification of textures and