Application of Extension Theory to PD Pattern Recognition in High-Voltage Current Transformers

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***Abstract*—This paper presents a novel partial-discharge (PD) recognition method based on the extension theory for high-voltage cast-resin current transformers (CRCTs). First, a commercial PD detector is used to measure the three-dimensional (3-D) PD patterns of the high-voltage CRCTs, then three data preprocessing schemes that extract relevant features from the raw 3-D-PD patterns are presented for the proposed PD recognition method. Second, the matter-element models of the PD defect types are built according to PD patterns derived from practical experimental results. Then, the PD defect in a CRCT can be directly identified by degrees of correlation between the tested pattern and the matter-element models which have been built up. To demonstrate the effectiveness of the proposed method, comparative studies using a multilayer neural network and k-means algorithm are conducted on 150 sets of field-test PD patterns of 23-kV CRCTs with rather encouraging results.**

***Index Terms*—Current transformers (CTs), extension theory, matter-element model, partial discharge (PD).**

I. Introduction

PARTIAL-DISCHARGE (PD) recognition is an important tool for evaluating the insulating capability of high-voltage (HV) power apparatus [1]–[3]. PD happens when the local electric field exceeds the threshold value and produces a partial breakdown of the surrounding medium, and it is a symptom and a cause of insulation deterioration. Therefore, PD testing can be used as an insulation diagnosis tool with the aim to optimize both maintenance and life-risk management in the power utilities [3]–[8].

The quantities of PD can carry information about the insulating system's condition to the outside world by their electrical signals. Using commercial PD detectors can generally produce PD pulses on an elliptic time base, and an experienced expert can use the PD patterns to identify the defect types in the tested apparatus. The main parameters of the PD patterns are phase angle ϕ and discharge magnitude q.

Various pattern clustering techniques, including expert systems (ES) [11], fuzzy clustering [12], and neural networks (NN) [1], [2], [13], [14] have been extensively used in PD recognition. Combinations of personal computers (PCs) and expert and fuzzy systems bring up the possibilities of automating recognition. However, it is hard to use these rule-based methods to acquire pictorial knowledge and hard to maintain the database of decision rules. MNNs with backpropagation algorithms have been successfully used in PD automated recognition since the latter half of 1991. The main advantage of an MNN over other classifiers is that it can directly acquire experience from the training data, and overcome some of the shortcomings of the expert system. However, the training data must be sufficient and compatible to ensure proper training; its convergence of learning is influenced by the network topology and values of learning parameters. A further limitation of the MNN approach is the inability to produce linguistic output, because it is difficult to understand the content of network memory.

To overcome the limitations of the ES and MNN mentioned above, a new PD recognition method, based on the extension theory, is presented for high-voltage CRCTs in this paper. The extension theory concept was first proposed by Cai to solve contradictions and incompatibility problems in 1983 [15]. Extension theory consists of two parts: matter-element model and extended set theory. With the combination of extension theory and management science, cybernetics, information science, and computer science, extension engineering methods have been applied to some engineering fields, such as economic engineering, management engineering, decision processes, and process control [16], [17]. Now, extension theory has been used in the research field of artificial intelligence (AI) and its relevant sciences. In this paper, we will first attempt to apply the extension theory to PD recognition. First, three data preprocessing schemes that extract the relevant features from the raw three-dimensional (3-D) PD patterns are presented for the proposed PD recognition method. Second, the matter-element models of the PD defects are built according to PD patterns derived from practical experimental results; then, the PD defects in CRCTs can be directly identified by degrees of correlation between the obtained patterns and the built-up matter-element models. To demonstrate the effectiveness of the proposed method, 150 sets of field-test PD patterns from 23-kV CRCTs were tested. Results of the studied cases show that the proposed method is suitable as a practical solution.

II. Outline of Extension Theory

Extension theory is a new kind of knowledge system based on the concepts of matter-elements and extension sets. It was first proposed by Cai to solve contradictions and incompatibility problems in 1983 [15]. The hard core of extension theory is two theoretical pillars that include matter-element theory and the theory of extension set. The former studies matter-elements and their transformations; it can be easy to represent the nature of the matter. The latter is the quantitative tool of extension

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theory; it can represent the correlation degree of two matter-elements in the designed correlation functions. The combination of these two pillars with other science generates the respective knowledge, which is the soft part of extension theory. Extension theory makes it possible to develop formalized descriptions for activities of creative thinking, such as knowledge innovation, new product design, and strategy generation [17]. Some definitions of extension theory are introduced in the next section.

A. Matter-Element Theory

In extension theory, a matter element uses an ordered triad as the basic element for describing things as follows:

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

where N represents the matter; c reprsents the characteristics; v is N's measure of the characteristics c, where v can be a value or an interval. If we assume that $R = (N, C, V)$ is a multidimensional matter-element, $C = [c_1, c_2, \ldots, c_n]$ is a characteristic vector and $V = [v_1, v_2, \ldots, v_n]$ is a value vector of C, then a multidimensional matter element is defined as

$$R = (N, C, V) = \begin{bmatrix} R_1 \\ R_2 \\ \cdots \\ R_n \end{bmatrix} = \begin{bmatrix} N, c_1, v_1 \\ c_2, v_2 \\ \cdots\cdots \\ c_n, v_n \end{bmatrix} \tag{2}$$

where $R_i = (N, c_i, v_i)$ $(i = 1, 2 \ldots n)$ is defined as the sub-matter element of R. For example

$$R = \begin{bmatrix} \text{John, Height,180 cm} \\ \text{Weight, 82 kg} \end{bmatrix}. \tag{3}$$

It can be used to state that John's height is 180 cm, and his weight is 82 kg. Matter has many characteristics, and one characteristic or one characteristic element can be possessed by many matters, etc. Some basic formulations in extension theory can be expressed as follows:

Nature 1: A matter has many characteristics, called one matter many characteristics, written as

$$N \dashv (N, c, v) \dashv \{(N, c_1, v_1), (N, c_2, v_2), \ldots, (N, c_n, v_n)\} \tag{4}$$

which shows that matter N can have characteristics $C_1, C_2, \ldots, C_n$. The symbol "$\dashv$" indicates the mean of the extension.

Nature 2: One characteristic can be possessed by many matters, called one characteristic many matters, written as

$$(N, c, v) \dashv \{(N_1, c, v_1), (N_2, c, v_2), \ldots, (N_n, c, v_n)\}. \tag{5}$$

Nature 3: One characteristic-element can be possessed by many matters, called one characteristic-element many matters, written as

$$(N, c, v) \dashv \{(N_1, c_1, v), (N_2, c_2, v), \ldots, (N_n, c_n, v)\}. \tag{6}$$

Using the matter-element model, we can describe the quality and quantity of a matter, which is a new concept in mathematical territory.

B. Summary of Extension Set

Set theory is a kind of mathematical scheme that describes the classification and pattern recognition about an objective. A Cantor set describes the definiteness of matters; a fuzzy set describes the fuzziness of matters. The extension set extends the fuzzy set from [0, 1] to $(-\infty, \infty)$ [16]. 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.

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

$$\widetilde{E} = \{(x, y) | x \in U, y = K(x) \in (-\infty, \infty)\} \tag{7}$$

where $y = K(x)$ is called the correlation function for extension set $\widetilde{E}$. The $K(x)$ maps each element of U to a membership grade between $-\infty$ and ∞. An extension set $\widetilde{E}$ in U can be denoted by

$$\widetilde{E} = E^+ \cup Z_o \cup E^- \tag{8}$$

where

$$E^+ = \{(x, y) | x \in U, y = K(x) > 0\} \tag{9}$$

$$Z_o = \{(x, y) | x \in U, y = K(x) = 0\} \tag{10}$$

$$E^- = \{(x, y) | x \in U, y = K(x) < 0\}. \tag{11}$$

In (9)–(11), E^+, E^-, and Z_o are called, respectively, the positive field, negative field, and zero boundary in $\widetilde{E}$.

Definition 2: If $X_o = \langle a, b\rangle$ and $X = \langle f, g\rangle$ are two intervals in the real number field, and $X_o \subset X$, where X_o and X are the classical (concerned) and neighborhood domains, respectively. The correlation function in the extension theory can be defined as follows:

$$K(x) = \begin{cases} -\rho(x, X_o), & x \in X_o \\ \frac{\rho(x, X_o)}{\rho(x, X) - \rho(x, X_o)}, & x \notin X_o \end{cases} \tag{12}$$

where

$$\rho(x, X_o) = \left| x - \frac{a+b}{2} \right| - \frac{b-a}{2} \tag{13}$$

$$\rho(x, X) = \left| x - \frac{f+g}{2} \right| - \frac{g-f}{2}. \tag{14}$$

The correlation function can be used to calculate the membership grade between x and X_o. The extended membership function is shown in Fig. 1. When $K(x) \geq 0$, it indicates the degrees to which x belongs to X_o. When $K(x) < 0$, it describes the degree to which x does not belong to X_o. When $-1 < K(x) < 0$, it is called the extension domain, which means that the element x still has a chance to become part of the set if conditions change.

III. Proposed PD Pattern Recognition Method

A. Structure of the PD Measuring System

The structure of the used PD measuring system is shown in Fig. 2. It includes a commercial PD detector (TE 571), a PD analyzer, an Internet communication system, a capacitor coupling circuit, a high-voltage (HV) control system, and the tested high-voltage CRCT. The practical experimental circuit in the shielded laboratory is shown in Fig. 3. For testing purposes, four kinds of experimental defect with artificial insulation defects were purposely manufactured by an electrical manufac-

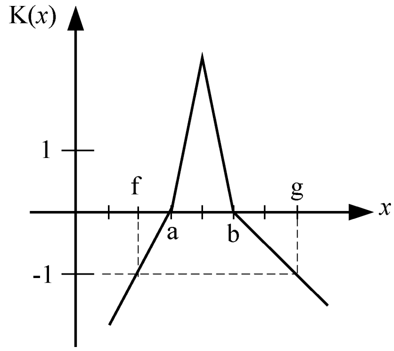


Fig. 1. Extended membership function.

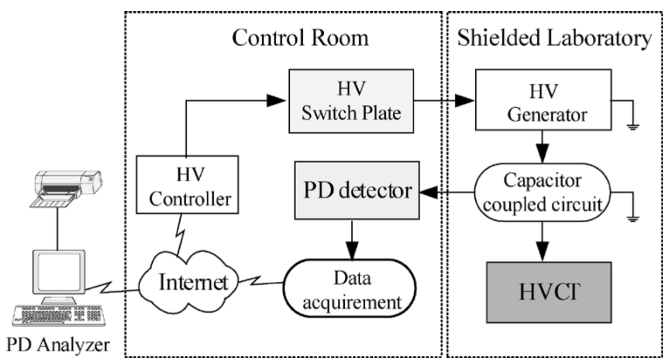


Fig. 2. PD measuring system diagram.

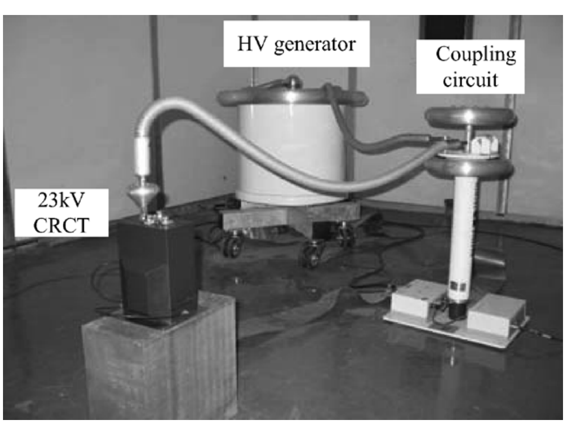


Fig. 3. Practical experimental circuit of PD test.

turer. These PD producing defect models include no defect (normal), low-voltage (LV) coil PD, HV corona discharge, and an HV coil PD. This testing system was set up in the Taiwan Electric Research and Testing Center (TERTC); that is an independent electrical testing institute in Taiwan. Fig. 4 shows a typical PD waveform in the window of the PD detector, which is most useful for an experienced maintenance engineer. In the testing process, all of the measuring data are analog-to-digital converted in order to store them in the computer memory. Then, the PD pattern analyzer can be programmed according to the digital PD signal with the setup program to recognize the defect type of the testing object.

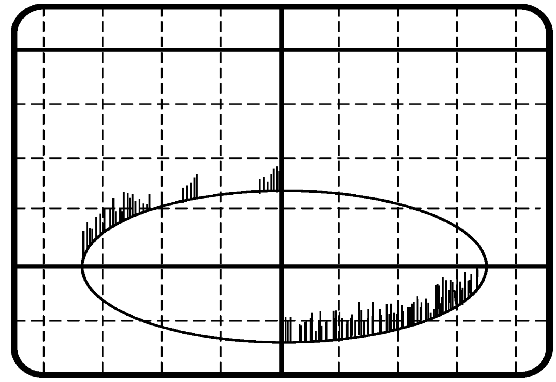


Fig. 4. Typical PD waveform in the PD detector [18].

B. Proposed Data Preprocessing Methods

The important parameters to depict PD patterns are phase angle ϕ, discharge magnitude q, and repetition rate n. These quantities can produce the 3-D patterns by virtue of advanced programs. The typical PD patterns of tested CRCTs in the testing field are shown in Fig. 5, in which the shape of a pattern is characteristic for a certain type of defect. Therefore, using the pattern recognition method allows the identification of different defect types in the tested CRCT. In previous studies, directly using the density distribution of 3D patterns with an MNN for PD recognition [13], [14], the main problem is that the structure of the MNN has a large number of neurons with connections due to the large amount of matrix elements; therefore, the MNN-based classifier takes a long time to train, and has poor generalization properties just because of containing too many free parameters. To improve the situation, three preprocessing schemes that extract relevant features from the raw PD patterns are presented in this paper. The detailed data manipulation process is shown in Fig. 6. A typical PD pattern is converted into ten represented values for ten phase windows. The width of every phase window is set to 36°. The represented value of every phase window can be calculated by three schemes as follows:

Scheme I: mean value of the total discharge magnitude

$$v_i = \frac{\sum_{j=1}^{m}\sum_{k=1}^{n} q_j n_{jk}}{\sum_{j=1}^{m}\sum_{k=1}^{n} n_{jk}}, \qquad \text{for } i = 1, 2, \ldots, 10. \tag{15}$$

Scheme II: mean value of the maximum discharge magnitude

$$v_i = \frac{\sum_{j=1}^{m} q_j n_j \max}{\sum_{j=1}^{m} n_j \max}, \qquad \text{for } i = 1, 2, \ldots, 10 \tag{16}$$

$$n_{j\,\max} = \max\{\mathrm{n_{jk}}\}. \tag{17}$$

Scheme III: maximum discharge magnitude

$$v_i = q_{j^*} \times n_{j^*\max}, \qquad \text{for } i = 1, 2, \ldots, 10 \tag{18}$$

where

$$n_{j^*\max} = \max\{n_{j^*k}\} \tag{19}$$

$$q_{j^*} = \max\{q_j\}. \tag{20}$$

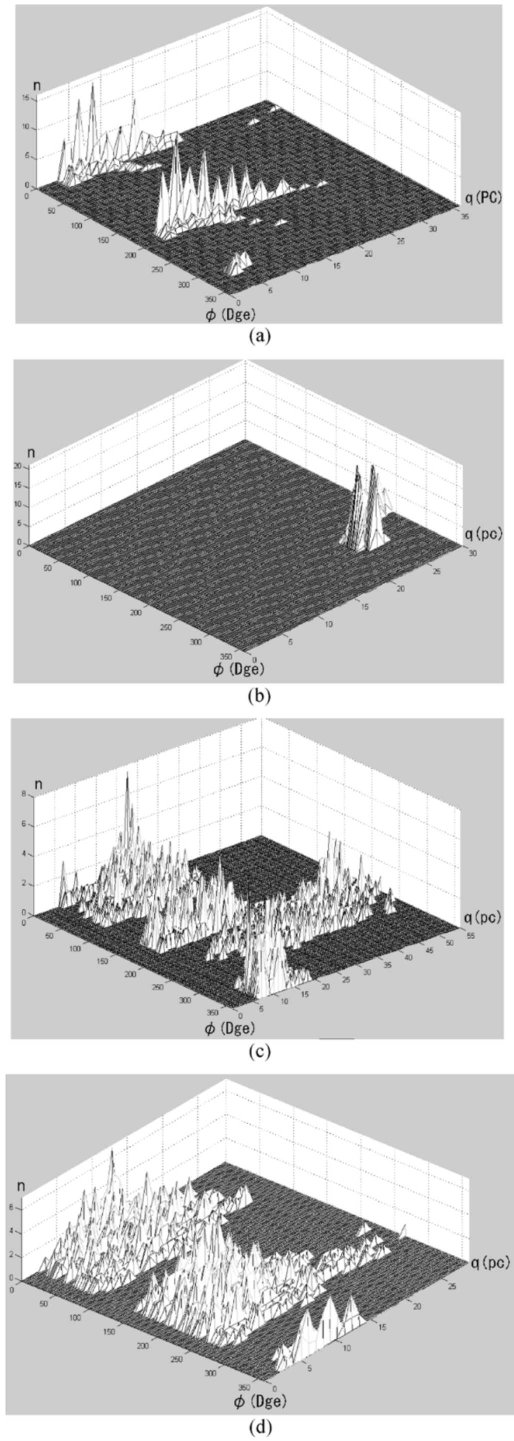


Fig. 5. Four typical defect types of PD pattern. (a) No defect (normal). (b) HV corona discharge. (c) LV coil PD. (d) HV coil PD.

When the preprocessing of the PD pattern has been completed, then the PD recognition stage can be started.

C. Extension PD Recognition Method

In this paper, the proposed PD recognition method is based on the extension theory; it is called the extension PD recognition method (EPDRM). The first step of the EPDRM is to formulate matter-element models of defect types, and then defect

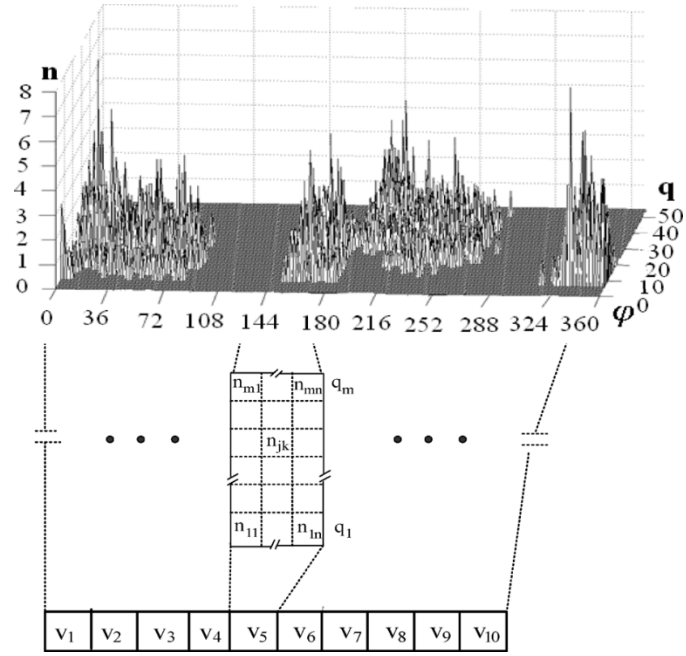


Fig. 6. Proposed date preprocessing schemes.

types of tested CRCTs can directly be identified by the degree of extended correlation function. The proposed EPDRM has been successfully implemented using PC-based software for defect recognition of high-voltage CRCTs. The proposed EPDRM is described as follows.

Step 1) Formulating the matter-element of every typical defect type as follows:

$$\begin{aligned} R_i &= (T_i, C_i, V_i) \\ &= \left\{ \begin{array}{lr} T_i, & c_1,\ \langle a_{i1}, b_{i1}\rangle \\ & c_2,\ \langle a_{i2}, bi2\rangle \\ & c_3, \langle a_{i3}, bi3\rangle \\ & c_4,\ \langle a_{i4}, bi4\rangle \\ & c_5,\ \langle a_{i5}, b_{i5}\rangle \\ & c_6,\ \langle a_{i6}, b_{i6}\rangle \\ & c_7,\ \langle a_{i7}, b_{i7}\rangle \\ & c_8,\ \langle a_{i8}, b_{i8}\rangle \\ & c_9,\ \langle a_{i9}, b_{i9}\rangle \\ & c_{10},\ \langle a_{i10}, b_{i10}\rangle \end{array} \right\}, \\ &\text{for } i=1,2,\ldots,4. \end{aligned} \tag{21}$$

where

- T_i ith defect type of PD pattern;
- c_j jth phase window;
- a_{ij} low-bounds value of classical domains in the jth phase window for ith defect type;
- b_{ij} the upbounds value of classical domains in the jth phase window for ith defect type.

The ranges of classical domains $V = \langle a, b\rangle$ of every phase window can be directly obtained from the low bounds and upbounds of field-test records, or determined from previous experience. Then, the neighborhood domain $\hat{V} = \langle f, g\rangle$ of classical domains, the possible range values of every characteristic can be determined. They are set as $f = 0.95 \times a$ and $g = 1.05 \times b$ in this paper.

Step 2) Input a PD pattern of tested CRCT; and formulating the matter-element of the PD pattern as follows:

$$R_t = (T_t, C_t, V_t) = \left\{ \begin{array}{ll} T_t, & c_1,\ v_{t1} \\ & c_2,\ v_{t2} \\ & c_3,\ v_{t3} \\ & c_4,\ v_{t4} \\ & c_5,\ v_{t5} \\ & c_6,\ v_{t6} \\ & c_7,\ v_{t7} \\ & c_8,\ v_{t8} \\ & c_9,\ v_{t9} \\ & c_{10},\ v_{t10} \end{array} \right\} \tag{22}$$

where $v_{t1}, v_{t2}, \ldots, v_{t10}$ are the values of tested PD pattern in every phase window that can be calculated by one of three schemes, as in Section III-B.

Step 3) Calculating the degrees of correlation of the tested CRCT set with the characteristic of the typical defects by the proposed extended correlation function as follows:

$$K_{ij}(v_{tj}) = \begin{cases} \frac{-2\rho(v_{tj}, V_{ij})}{|b_{ij} - a_{ij}|}, & \text{if } v_{tj} \in V_{ij} \\ \frac{\rho(v_{tj}, V_{ij})}{\rho(v_{tj}, \hat{V}_{ij}) - \rho(v_{tj}, V_{ij})}, & \text{if } v_{tj} \notin V_{ij} \end{cases}$$
$$i = 1, 2, \ldots, 4; \quad j = 1, 2, \ldots, 10 \tag{23}$$

where

$$V_{ij} = \langle a_{ij}, b_{ij} \rangle \tag{24}$$
$$\hat{V}_{ij} = \langle f_{ij}, g_{ij} \rangle. \tag{25}$$

The proposed extended correlation function can be shown as in Fig. 7, where $0 \leq K(v) \leq 1$ corresponds to the normal fuzzy set. It describes the degree to which v belongs to V. When $K(v) < 0$, it indicates the degree to which v does not belong to V, which is not defined in the fuzzy theory and is a main advantage of the extension theory.

Step 4) Setting the weights of every degree of correlation $W_1, W_2, \cdots, W_{10}$, depending on the importance of every feature in the recognition process. In this paper, all ten weights are set at 1/10.

Step 5) Calculating the indexes of correlation for every defect type

$$\zeta_i = \sum_{j=1}^{10} W_j K_{ij}, \quad i = 1, 2, \ldots, 4. \tag{26}$$

Step 6) Normalizing the indexes of correlation into an interval between -1 and 1 as (27). This process will be beneficial for fault diagnosis

$$\lambda_i = \frac{2\zeta_i - \zeta_{\min} - \zeta_{\max}}{\zeta_{\max} - \zeta_{\min}}, \quad i = 1, 2, \ldots, 4 \tag{27}$$

where

$$\zeta_{\max} = \max_{1 \leq i \leq 4} \{\zeta_i\} \tag{28}$$
$$\zeta_{\min} = \min_{1 \leq i \leq 4} \{\zeta_i\}. \tag{29}$$

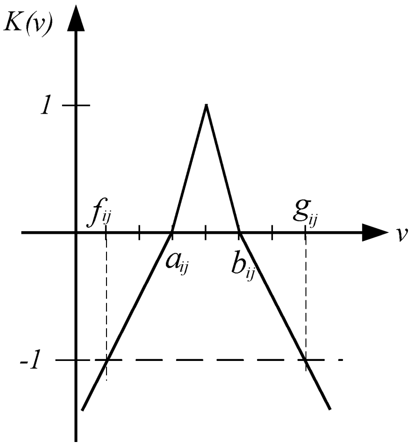


Fig. 7. Proposed extended correlation function.

Step 7) Ranking the normalized defect indexes, and finding the maximum index of correlation (or 1) to detect the defect type of the tested CRCT. The defect recognition rule is shown as follows:

$$\text{IF } (\lambda_k = 1) \text{ THEN } (T_t = T_k) \tag{30}$$

Equation (30) expresses that if $\lambda_k = 1$, then the defect type of this tested CRCT is kth defect type.

Step 8) Going back to step 2) for the next tested CRCT when the recognition of one has been completed, until all have been done.

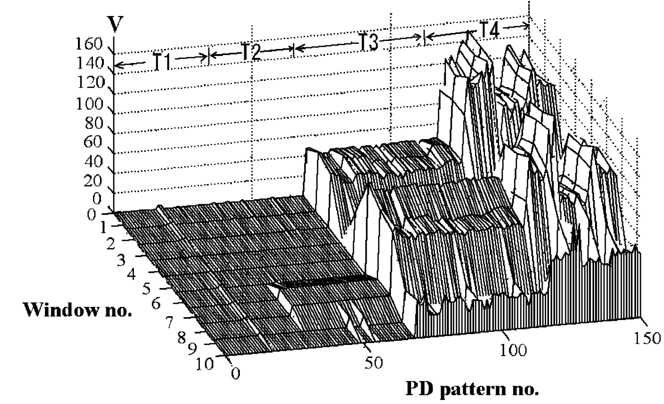
The main advantage of the proposed method is that it can provide more detailed information about the defect type of the tested CRCT set by indexes of correlation. It is also the proposed method that can determine the main fault severity compared to other types, and identify the defect likelihood by the fault indexes. It is most helpful in the diagnosis of multiple defects. Moreover, the proposed method does not need to learn or to tune any parameters, and a simple software package can easily implement it.

IV. Experimental Results and Discussion

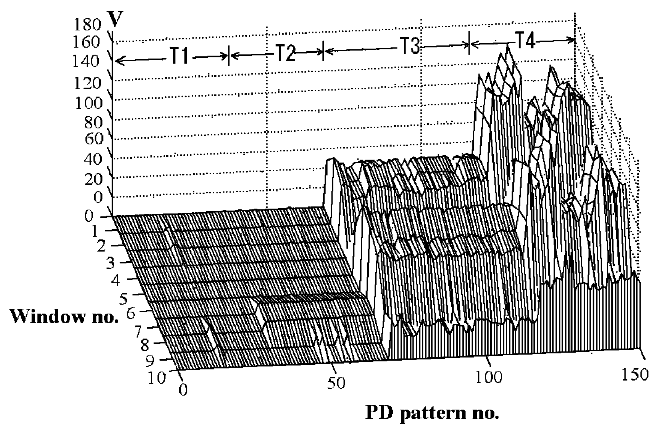
The proposed method has been implemented according to the field-test PD pattern collected from TERTC. Associated with their real defect types, there is a total of 150 sets of sample data under different testing conditions. The testing process followed the IEC60270 Standard [18]. The tested objects are some EWF-20 DB types of CRCTs that use epoxy resin for HV insulation. The rated voltage and current of the tested CRCTs are 23 kV and 60 A/5 A, respectively. Some experimental results are shown as follows.

A. Results of the Data Preprocessing

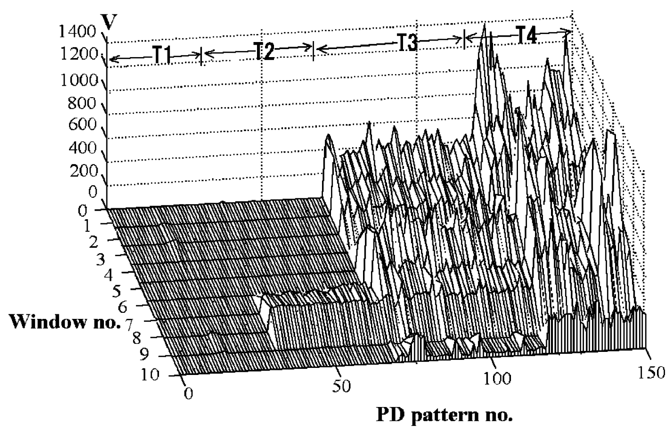
As stated in Section III-B, Fig. 8 shows the 150 input patterns of the four defect models produced by the three data preprocessing methods. It is clear that the input patterns of scheme I are similar to the input patterns of scheme II, and the four defect models have quite different patterns after data processing. It is



(a)



(b)



(c)

Fig. 8. Typical input patterns of four PD defects with different data preprocessing schemes. (a) PD patterns of scheme I. (b) PD patterns of scheme II. (c) PD patterns of scheme III.

very clear in Fig. 8 that the input patterns of no defect (a range of T_1) have the lower discharge magnitude in all observed phase windows; the input patterns of HV corona discharge (range of T_2) have the high discharge magnitude in six, seven, eight, and nine windows. The input patterns of LV coil PD (range of T_3) have higher discharge magnitudes in one, two, six, and seven windows. Oppositely, the input patterns of HV coil PD (T_4) have higher discharge magnitudes in one, two, three, and five to seven windows. It is shown that the proposed data preprocessing schemes will be most useful for PD pattern recognition.

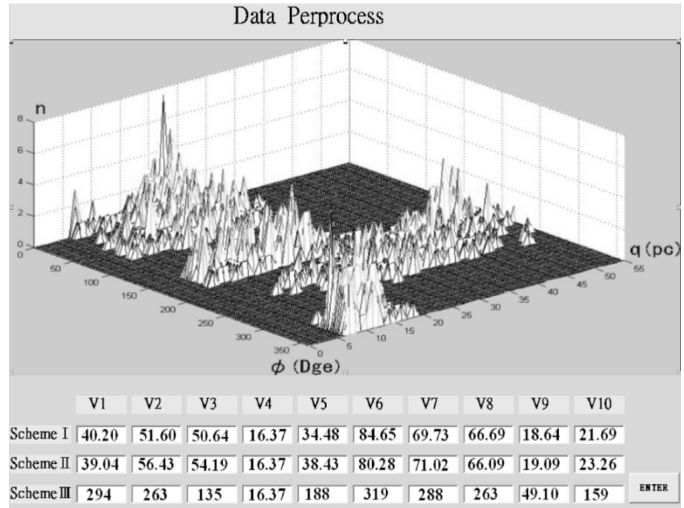


Fig. 9. Typical windows of the proposed PD recognition system.

TABLE I
PARTIAL RECOGNITION RESULTS

Pattern no.	Correlation Indexes				Defect Types
	λ_1	λ_2	λ_3	λ_4	
1	1	-0.07	-0.65	-1	Normal
2	1	-0.12	-0.61	-1	Normal
3	1	-0.40	-0.57	-1	Normal
34	-1	1	-0.10	-0.21	HV corona discharge
35	-1	1	-0.02	-0.12	HV corona discharge
70	-1	-0.86	1	0.28	LV coil PD
71	-0.49	-1	1	0.83	LV coil PD
118	-0.62	-1	-0.88	1	HV coil PD
119	-0.65	-1	-0.97	1	HV coil PD
120	-1	-0.84	-0.26	1	HV coil PD

* λ_1 : Correlation index of defect type no. 1 (i.e. Normal).

* λ_2 : Correlation index of defect type no. 2 (i.e. HV corona discharge).

* λ_3 : Correlation index of defect type no. 3 (i.e. LV coil PD).

* λ_4 : Correlation index of defect type no. 4 (i.e. HV coil PD).

B. Software of the Automated PD Recognition System

The proposed method has been implemented by windows-based software in a Pentium IV-PC. Fig. 9 shows a typical window of automated recognition software; there a typical PD pattern has been converted into ten represented values for ten phase windows by the proposed data preprocessing schemes. The processed data will be sent to the next stage for PD recognition. Table I shows partial results of the proposed PD recognition system. It very clearly recognizes the defect types of tested CRCT. For example, in pattern 1, the index of correlation with the defect type 1 (i.e., normal or no defect) equals 1 (or maximum value), which is indicative of no defect (i.e., normal). In comparison, the indexes of correlation with other defect types are all negative values; therefore, CRCT no. 1 does not need to be checked in the future. Moreover, the proposed method cannot only detect the main defect of the tested object; it can also provide useful information for future trend analysis by the indexes of correlation. For example, pattern no. 71 was recognized to have a main defect type of LV coil PD

TABLE II
RECOGNITION PERFORMANCES OF DIFFERENT METHODS WITH DIFFERENT PERCENTAGES OF ERRORS ADDED

Perce. of errors	Recognition rate (%)				
	MNN	K-means*	Proposed methods #		
			Scheme I	Scheme II	Scheme III
± 0%	100%	92%	100%	100%	100%
± 5%	98%	75%	100%	100%	98%
± 10%	96%	73%	100%	100%	97%
± 15%	93%	70%	100%	100%	96%
± 20%	88%	68%	100%	100%	95%
± 25%	85%	67%	98%	98%	95%
± 30%	80%	64%	96%	93%	93%

*Average of 10 random trials.
#Scheme I: using scheme I of data preprocessing with the proposed EPDRM.
#Scheme II: using scheme II of data preprocessing with the proposed EPDRM.
#Scheme III: using scheme III of data preprocessing with the proposed EPDRM.

due to the maximum index of correlation with defect type no. 3 (i.e., λ_3). On the other hand, the index of correlation λ_4, about 0.83, also shows that this CRCT had a medium possibility of defect type no. 4 (i.e., HV coil PD). Conversely, because of a negative index of correlation, CRCT no. 71 had a very low possibility of defect type no. 2 (i.e., HV corona discharge). This information will be most useful to find the hidden defects of CRCT for a maintenance engineer.

C. Recognition Accuracy of the EPDRM

The input data to a PD recognition system would unavoidably contain some amounts of noise and uncertainties. The sources of error include environmental electromagnetic (EM) noise, transducers, human mistakes, etc. To take into account noise and uncertainties contained in the data collected for PD pattern recognition, 150 sets of testing data in this paper were created by adding $\pm5\%$ through $\pm30\%$ random uniformly distributed samples to the testing data to appraise the noise-tolerant abilities of the proposed EPDRM. The test results using different amounts of error added are given in Table II with the different recognition methods. Usually, the error containing data indeed degrade the recognition capabilities in proportion to the amounts of error added. This table shows that these methods all show high tolerance to the errors contained in the data. The proposed method with schemes I and II has a significantly higher recognition accuracy of 100% with $\pm20\%$ errors added, but the accuracy of scheme III is lower than the other schemes. However, the proposed methods with all three data preprocessing schemes show good tolerance to added errors, and have accuracies of 96% to 93% in the case of $\pm30\%$ added error. Contrarily, the accuracy of an MNN-based method [11] and k-means algorithm [19] are, respectively, only 80% and 64% in the same conditions. Moreover, the proposed method does not need to learn, but only to find the low bound and upperbound of the input features. This is rather beneficial when implementing the PD recognition methods in a microcomputer for a real-time PD detecting device or a portable instrument.

V. CONCLUSION

This paper presents a novel PD recognition method based on the extension theory and three data preprocessing schemes for PD recognition in high-voltage CRCTs. Compared with other traditional methods, the proposed method does not require particular artificial parameters and learning processes. In addition, the calculation of the proposed recognition algorithm is fast and very simple. It can be easily implemented by PC-based software. According to the experimental results, schemes I and II of data preprocessing are suggested for PD recognitions due to higher accuracy and error tolerances. Test results show that the proposed method cannot only recognize the main defect type of the tested object; it can also detect useful information for future trends and multidefects analysis by the correlation indexes. This new approach merits more attention, because extension theory deserves serious consideration as a tool in PD recognition problems. We hope this paper will lead to further investigation for other applications.

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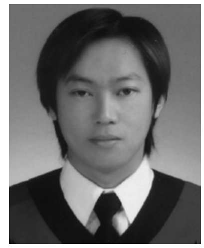

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