Partial Discharge Classification Using Neural Networks and Statistical Parameters

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Abstract: - Partial discharge (PD) pattern recognition is an important tool in high-voltage insulation diagnosis of power systems. A PD pattern classification approach of high-voltage power transformers based on a neural network is proposed in this paper. A commercial PD detector is firstly used to measure the 3-D PD patterns of epoxy resin power transformers. Then, the gray intensity histogram extracted from the raw 3-D PD patterns are statistically analyzed for the neural-network-based (NN-based) classification system. The system can quickly and stably learn to categorize input patterns and permit adaptive processes to access significant new information. To demonstrate the effectiveness of the proposed method, the classification ability is investigated on 120 sets of field tested PD patterns of epoxy resin power transformers. Different types of PD within power transformers are identified with rather encouraged results.

Key-Words: - Partial Discharge, Pattern Classification, Neural Network, Statistical Parameter.

1 Introduction

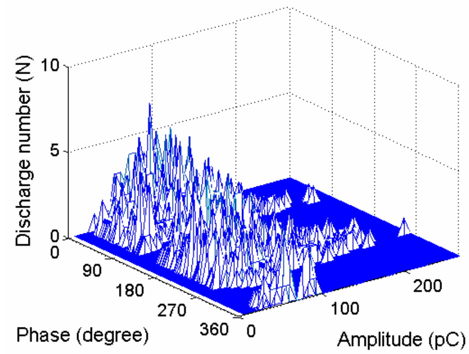
Power transformers play a crucial role in operation of transmission and distribution systems. A dielectric failure in a power transformer could result in unplanned outages of power systems, which affects a large number of customers [1]. Therefore, it is of great importance to detect incipient failures in power transformers as early as possible, so that they can be switched safely and improve the reliability of the power systems. Partial discharges phenomenon usually originates from insulation defects and is an important symptom to detect incipient failures in power transformers. Classification of different types of PDs is of importance for the diagnosis of the quality of HV power transformers. PD behavior can be represented in various ways. Because of the randomization of PD activity, one of the most popular representations is the statistics-based φ-Q-N distribution, i.e., the PD pattern is described using a pulse count N versus pulse height Q and phase angle φ diagram. Previous experimental results have adequately demonstrated that φ-Q-N distributions are strongly dependent upon PD sources, therefore the 3-D patterns can be used to characterize insulation defects [2]. This provides the basis for pattern recognition techniques that can identify the different types of defects.

The automated recognition of PD patterns has been widely studied recently. Various pattern recognition techniques have been proposed, including expert systems [3], fuzzy clustering [4], and neural networks (NNs) [5], [6]. The expert system and fuzzy approaches require human expertise, and have been successfully applied to this field. However, there are some difficulties in acquiring knowledge and in maintaining the database. NNs can directly acquire experience from the training data, and overcome some of the shortcomings of the expert system. However, the raw values of 3-D patterns were used with the NN for PD recognition in previous studies [7], the main drawbacks are that the structure of the NN has a great number of neurons with connections, and time-consuming in training. To improve the performance, the gray intensity histogram [8] that extract relevant characteristics from the raw 3-D PD patterns are statistically analyzed for the proposed NN-based classifier. Four statistical features including skewness, kurtosis, coefficient of standard deviation, and correlation coefficient [9] are calculated based on this gray intensity histogram. The fault diagnosis database is built in accordance with the statistical features extracted. The proposed NN-based classifier can then quickly and stably learn to categorize input patterns and permit adaptive processes to access significant new information. To demonstrate the effectiveness of the proposed method, 120 sets of field-test PD patterns from high-voltage epoxy resin power transformers are tested. Results of the studied cases show that different types of PD within power transformers are identified with rather encouraged results.

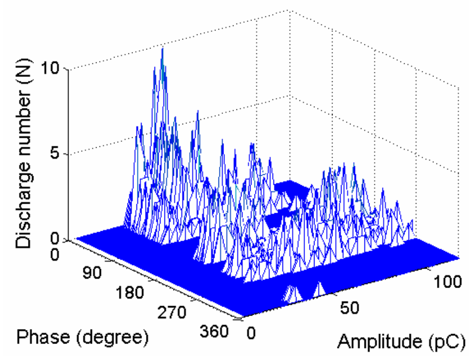
2 Partial Discharge Experiments and Pattern Processing

In this paper, the tested object is an cast-resin high-voltage power transformers that uses epoxy resin for high-voltage insulation. The rated voltage and capacity of the tested HV power transformers are 12kV and 2kVA, respectively. For testing purposes, four experimental models of power transformers with artificial insulation defects were purposely manufactured by an electrical manufacturer. The four PD models, including high voltage (HV) coil PD, low voltage (LV) coil PD, HV corona discharge, and no defect are named Type I, II, III, and IV, respectively. In the testing process, all of the measuring data are digitally converted in order to store them in the computer. Then, the PD pattern classifier can automatically recognize the different defect types of the testing objects.

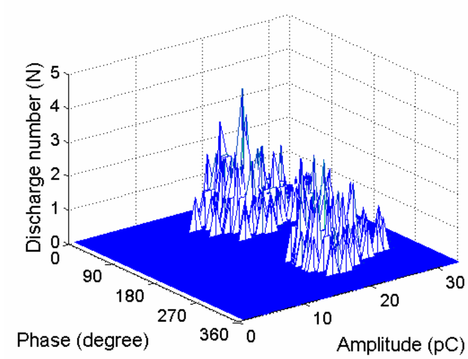
The individual 3-D PD patterns (stored as a 256x256 matrix) are plotted. The x and y axes correspond to the phase and amplitude (or charge), respectively. The matrix elements correspond to the pulse count data (or the z axis of the 3-D pattern). An example 3-D plot of the pattern from each one of the four types is given in Fig. 1. In order to simplify the extraction of the statistical features, a real gray-scaled image would be utilized instead of 3-D patterns. The amplitude values are linearly mapped to the varying intensities of the white color (uniformly mapped to one of the 16 gray colors in this work). This gray image is then converted to gray intensity histogram for further statistical analysis. An intensity histogram is a graph. The histogram of an image normally refers to a histogram of the pixel intensity values. This histogram shows the number of pixels in an image at each different intensity value found in that image. For a 4-bit gray-scale image there are 16 different possible intensities, and so the histogram will graphically display 16 numbers showing the distribution of pixels amongst those gray-scale values. Fig. 2 shows the corresponding gray-scaled image and gray intensity histogram of HV coil PD (Type I) in Fig. 1(a).



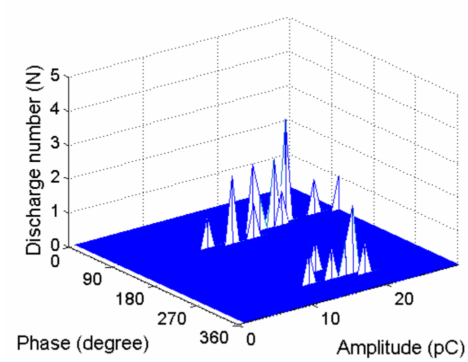
(a)



(b)

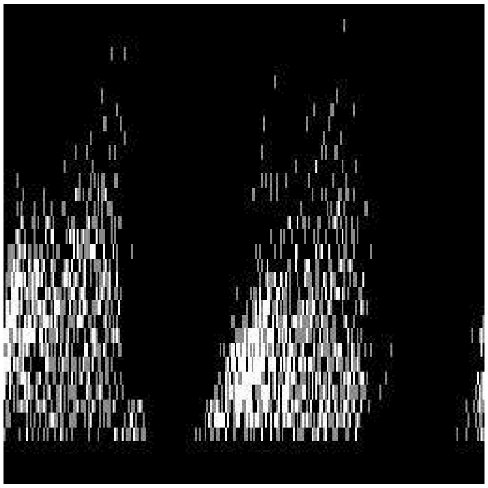


(c)

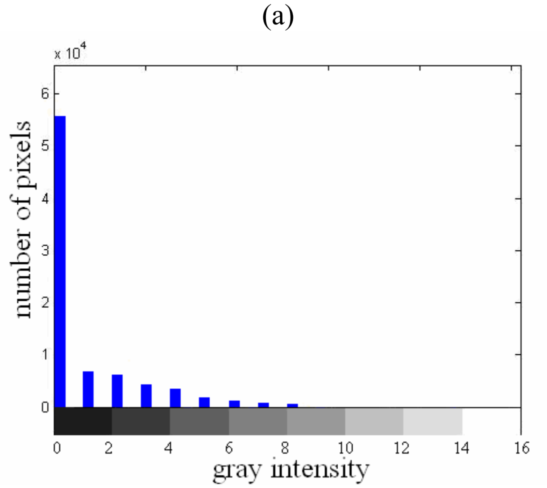


(d)

Fig. 1 Four typical defect types of PD pattern. (a) HV coil PD (Type I). (b) LV coil PD (Type II). (c) HV corona discharge (Type III). (d) no defect (Type IV)



(a)



(b)

Fig. 2 The corresponding gray-scaled image and gray intensity histogram of HV coil PD (Type I) in Fig. 1(a)

3 Statistical Features Analysis of Gray Intensity Histogram

The shape of the histogram provides us with information about the nature of the image. The features of the histogram that we consider here are statistical characteristics, where the histogram is used as a model of the probability distribution of the gray levels. These statistical features provide us with information about the characteristics of the gray level distribution for the image. In this work, three statistical features including skewness, kurtosis, and coefficient of standard deviation are all calculated based on the gray intensity histogram. The correlation coefficient is calculated based on the gray-scaled image. These statistical features are defined as follows [8], [9].

A. skewness (SK)

It measures the asymmetry about the mean in the gray intensity histogram. It is defined as

$$SK(x_1,...,x_N)=\sum_{i=1}^{N}\left[\frac{x_i-\mu}{\sigma}\right]^3\cdot P_i \tag{1}$$

where x_i is the *i*-th gray value and P_i is the probability of appearance for *i*-th gray value, i.e. *i*-th gray intensity value. μ is the mean value and σ is the variance. N is the number of possible gray intensity values, which is 16 in this work. The positive skewness indicates the distribution is skewed to the left, with a longer tail to the right of the distribution maximum. Negative skewness indicates the distribution is skewed to the right, with a longer tail to the left of the distribution maximum. The skewness shows how symmetry the distribution.

B. kurtosis (KU)

It measures the sharpness about the mean in the gray intensity histogram. It is defined as follow

$$KU(x_1,...,x_N)=\sum_{i=1}^{N}\left[\frac{x_i-\mu}{\sigma}\right]^4\cdot P_i-3 \tag{2}$$

The positive kurtosis indicates a relatively peaked distribution. Negative kurtosis indicates a relatively flat distribution, and normal distributions produce a kurtosis statistic of about zero.

C. coefficient of standard deviation (CV)

The coefficient of standard deviation is a measurement of dispersion of a probability distribution. It is defined as the ratio of the standard deviation to the mean

$$CV(x_1,...,x_N)=\frac{\sigma}{\bar{x}} \tag{3}$$

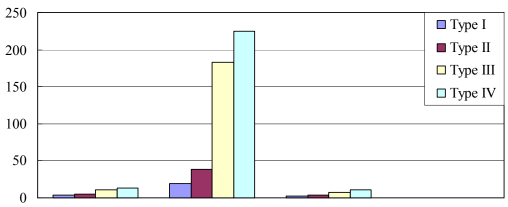
D. correlation coefficient (r)

The gray-scaled image is divided into positive and negative half cycles in according to phase. The correlation coefficient describes the difference in distribution shape between these two cycles. It is defined as follow

$$r=\frac{\sum_{i=1}^{M_p}\sum_{j=1}^{M_a}x_{ij}\,y_{ij}-\left(\sum_{i=1}^{M_p}\sum_{j=1}^{M_a}x_{ij}\sum_{i=1}^{M_p}\sum_{j=1}^{M_a}y_{ij}\right)/(M_pM_a)}{\sqrt{\sum_{i=1}^{M_p}\sum_{j=1}^{M_a}x_{ij}^2-\left(\sum_{i=1}^{M_p}\sum_{j=1}^{M_a}x_{ij}\right)^2/(M_pM_a)}\sqrt{\sum_{i=1}^{M_p}\sum_{j=1}^{M_a}y_{ij}^2-\left(\sum_{i=1}^{M_p}\sum_{j=1}^{M_a}y_{ij}\right)^2/(M_pM_a)}} \tag{4}$$

where x_{ij} is the gray value at *ij*-th position of the positive half cycle and y_{ij} is the gray value in the corresponding negative half cycle. M_p is the number of pixel of each half cycle at *x* axes and M_a is the number of pixel at *y* axes. The coefficient ranges from -1 to 1. The value of *r* represents the degree of symmetry between positive and negative half cycle of a distribution.

According to these definition, the average values of the statistical parameters corresponding to the four types of field-test PD patterns are calculated and shown in Fig. 3. Starting with PD patterns on different types of specimens, a suitable set of statistical parameters are determined and then used as input variables to a neural network foe the purpose of classifying the defects within the insulation.



	SK	*KU*	*CV*	*r*
Type I	3.9176	19.604	2.9684	0.3337
Type II	5.2253	38.587	3.5955	0.0602
Type III	10.452	183.23	7.2656	0.3576
Type IV	13.154	224.66	10.637	0.2321

Fig. 3 Average values of statistical parameters of four types of field-test PD patterns

4 Recognition Results and Discussion

The problem in this paper is how to classify the type of defect that produced those PD data. In this aim, a multilayer artificial NN could appear certainly as the best solution that is possible to find. A back propagation neural network (BPNN) has been chosen because it is simple and easy to change the number of hidden layers and the number of neurons [10]. The BPNN utilized to classify PD pattern of the models is shown in Fig. 4. Four layers feed forward structure is used for the pattern classification system. A multilayer perceptron NN with two hidden layers can design arbitrary classification regions, the approximation being related to the number of hidden nodes [11]. The architecture of the BPNN is the result of many tests performed, and varying the number of neurons in the hidden layers. The neuron number of its input is determined by the number of statistical features, viz., skewness, kurtosis, coefficient of standard deviation, and correlation coefficient. The neuron number of both hidden layers is 6. The neuron number of output layer is determined by the number of patterns to be identified, which is 4 in this study. To demonstrate the classification ability, 120 sets of field test PD patterns are used to test the proposed PD classification system. The four defect models of 12-kV epoxy resin power transformers include the no-defect, HV corona discharge, LV coil PD, and HV coil PD, respectively. The NN-based PD classification system randomly chooses 80 instances from the field test data as the training data set, and the rest of the instances of the field test data are the testing data set. Table 1 shows the classified results of the proposed system with different input patterns. The recognition rates of the proposed system is quite high with 100%. It is obvious that the NN-based PD classification system has strong generalized capability.

The field test data would unavoidably contain some noise and uncertainties which originate in environmental noise, transducers, or human mistakes. To evaluate the fault tolerance ability, total 120 sets of noise-contained testing data are generated by adding ±5% to ±30% of random, uniformly distributed, noise to the training data to take into account the noise and uncertainties. The test results with different amounts of noise added are also shown in Table 1 for the BPNN. Usually, the noise-contained data indeed degrade the classification abilities in proportion to the amounts of noise added. The proposed classification system shows good tolerance to added noise, and has high accuracy rates of 80% in extreme noise of 30%. This table shows that the BPNN rather withstand remarkable tolerance to the noise contained in the data.

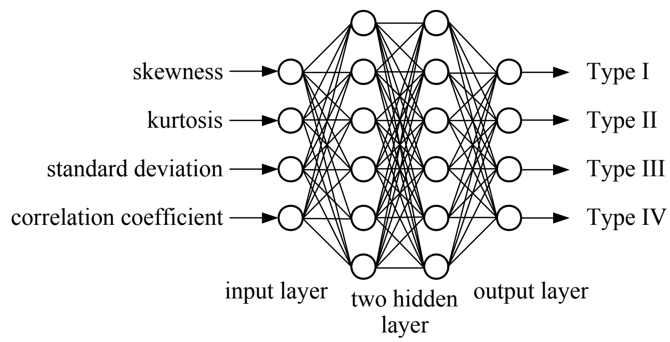


Fig. 4 Topology structure of back propagation NN-based pattern recognition system

Table 1 Classified performances of the BPNN with various noise added

Proportion of noise	Recognition rate (%)
± 0	100.0
± 5	97.5
± 10	92.5
± 15	90.0
± 20	85.0
± 25	82.5
± 30	80.0

5 Conclusion

A method to analyze a PD pattern and identify the type of discharge source is an important tool for the diagnosis of HV insulation system. A NN-based PD pattern classification system for HV power transformers is proposed. To improve the performance, the gray intensity histogram that extract relevant characteristics from the raw 3-D PD patterns are statistically analyzed for the proposed NN-based classifier. These statistical features are then applied to a neural network that performs the classification. The recognition rates of the proposed system are quite high with 100%, and 80% in extreme noise of 30%. The present experimental results indicate that this approach is able to implement an efficient classification with a very high recognition rate.

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References

[1] Feinberg R., *Modern Power Transformer Practice*, John Wiley & Sons, New York, 1979

[2] Krivda A., "Automated Recognition of Partial Discharge," *IEEE Trans. on Dielectrics and Electrical Insulation*, Vol.2, 1995, pp. 796-821.

[3] Satish L. and Gururaj B.I., "Application of Expert System to Partial Discharge Pattern Recognition," in CIGRE Study Committee 33 Colloquium, Leningrad, Russia, 1991, Paper GIGRE SC 33.91.

[4] Tomsovic K., Tapper M., and Ingvarsson T.T., "A Fuzzy Information Approach to Integrating Different Transformer Diagnostic methods," *IEEE Trans. on Power Delivery*, Vol.8, 1993, pp. 1638-1643.

[5] Cho K.B. and Oh J.Y., "An Overview of Application of Artificial Neural Network to Partial Discharge Pattern Classification," *Proc. of the 5th International Conference on Properties and Applications of Dielectric Materials*, Vol.1, 1997, pp. 326-330.

[6] Zhang H., Lee W.J., Kwan C., Ren Z., Chen H., and Sheeley J., "Artificial Neural Network Based On-Line Partial Discharge Monitoring System for Motors," *IEEE Conference of Industrial and Commercial Power Systems Technical*, 2005, pp. 125-132.

[7] Salama M.M.A. and Bartnikas R., "Determination of Neural Network Topology for Partial Discharge Pulse Pattern Recognition," IEEE Trans. on Neural Networks, Vol.13, 2002, pp. 446-456.

[8] Gonzalez R.C. and Wintz P., *Digital Image Processing*, Addison Wesley, Boston, 1987

[9] Li J., Sun C., and Yang, D.L., "PD Pattern Recognition Using Combined Features," *Proc. of IEEE International Symposium on Electrical Insulation*, Indiaanapolis, 2004, pp. 139-142.

[10] Wasserman P.D., *Neural Computing, Theory and Practice*, Van Nostrand Reinhold, 1989

[11] Hertz J., Krogh A., and Palmer, G.R., *Introduction to the Theory of Neural Computing*, Addison Wesley, Boston, 1991