Application of Self Organizing Map Approach for Partial Discharge Pattern Recognition of Insulators

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Abstract: This paper proposes a self organizing map (SOM) based recognition method to identify the insulation defects of electrical apparatus arising from partial discharge (PD). PD patterns are detected by a PD detecting system set up in the laboratory. The significant features of PD patterns are extracted by using the nonlinear principal component analysis (NLPCA) method. Based on the feature extracted, the SOM network is further employed for the PD pattern recognition. To verify the proposed approach, experiments are conducted to demonstrate the field-test PD pattern recognition of insulators by using 250 feature vectors of field-test PD patterns. Five types of models with artificial defects are purposely created to produce five common PD activities of insulators for the experiments. The practical results show that the proposed method is promising as a solution to the PD pattern recognition.

Keywords: Self organizing map; Nonlinear principal component analysis; Pattern recognition; Partial discharge; Insulators

INTRODUCTION

With influences of a sufficiently strong electric field, a sudden local displacement of electrons and ions leads to PD associated with a defect in an insulator [1]. A PD event that occurs in the epoxy resin insulator of electrical apparatus would have harmful effects on insulation that may finally cause failure of service. A defect of a electrical apparatus, as resulting in partial discharge, would have a corresponding particular pattern. Therefore, pattern recognition of PD is significant for insulation condition judgment of electrical apparatus.

Recently, many methods have been employed for the pattern recognition of PD, including back-propagation multilayer neural networks [1-3], expert systems [4], and fuzzy classification [5]. However, the training process of multilayer neural networks is often very slow, and the training data must be sufficient and compatible. The expert system method and the fuzzy classification method acquire the knowledge of human expertise to build knowledge base and fuzzy rule base. Such bases are difficult in building and maintaining.

To overcome the disadvantages mentioned above, the aim of this paper is at proposing a new SOM based pattern recognition technique for PD of electrical apparatus. The proposed recognition scheme is more effective and robust than the conventional pattern recognition methods.

This paper is organized as follows. After the introduction, PD pattern collecting and the algorithm of feature extraction are described. The principle of SOM and the procedure of proposed pattern recognition scheme are given subsequently. Then, presented are the experimental results and the analysis using 250 sets of field-test PD patterns from five artificial defect types of electrical apparatuses. From the results, effectiveness of the proposed scheme to improve the recognition accuracy has been demonstrated. Finally, conclusions are given.

PD PATTERN COLLECTING

In order to investigate the PD features and verify the classification capabilities of the SOM for different PD types commonly occurring in electrical apparatuses, a PD dataset is needed. The PD dataset was collected from laboratory tests on a series of model transformers. The material and process used to manufacture the model transformers were exactly the same as that of making a field electrical apparatus. Five types of experimental models with artificial defects embedded were purposely manufactured to produce five common PD events in the electrical apparatuses.

PD events were detected by a PD detecting system, which was built up in the laboratory. The configuration of the PD detecting system is shown in Fig. 1. It includes step-up transformer, capacitor coupling circuit, PD detector, and the electrical apparatus under test. Through the testing processes, all the data measured were digitally converted in order to save them in the computer memory. Then, 3-dimension patterns of PD derived from the original PD data are created according to the digital PD signal by using the programs developed. For the typical 3-dimension pattern of PD, the X-axis stands for the phase angle at PD onset, Y-axis for PD amount, and Z-axis for discharge count.

PD PATTERN FEATURE EXTRACTION

The surface of 3-dimension pattern is considered to be a fractal. Feature extraction is necessary in the PD pattern recognition to reduce dimension of original data and make effective discrimination of the 3-dimension...
patterns for different PD status. In this paper, the significant features are extracted by using NLPCA method [6-7]. The NLPCA is based on the structure of multiplayer neural networks model (DMNN), which contains four layers of nodes, as shown in Fig. 2.

In Fig. 2, the DMNN for NLPCA contains two subnetworks of mapping and demapping networks. The mapping from data space to feature space is referred to as the mapping network and the reverse mapping as the demapping network. The units at layers 1 and 3 of the network have sigmoid activation functions.

In training, the output vector $\mathbf{x} = [x_1, x_2, ..., x_n]$, where $n$ is the number of units at the output and input layers, is anticipated to approach the input data vector $\mathbf{x} = [x_1, x_2, ..., x_n]$ at the input layer. As noted, the input layer of the mapping network has units equal to the dimensionality of the input data. After the network is trained, the $m$ units at layer 2 represent lower-dimensional nonlinear features $\mathbf{f} = [f_1, f_2, ..., f_m]$ extracted from the input data set.

The NLPCA attempts to find the mappings from multidimensional data space to lower-dimensional feature space. In the process, the reconstruction error between input $\mathbf{x}$ and output $\mathbf{x}$ of the dual networks is minimized [6].

$$ J = \| \mathbf{x} - \hat{\mathbf{x}} \|^2 $$  

The whole network, consisting of the dual networks in the NLPCA, is an autoassociative network where the output vector corresponds to the input vector. The main advantage of NLPCA over principal component analysis is that NLPCA has the ability to stand for nonlinear relationships among the data set of variables.

**SOM-BASED PD PATTERN RECOGNITION METHOD**

In this section, algorithm of SOM and SOM-based PD pattern recognition scheme are described. The PD recognition through SOM in multidimensional feature space is also validated on the basis of the laboratory PD dataset as mentioned above.

**Algorithm of SOM**

SOM is a typical unsupervised neural network, which maps the multidimensional space onto a two dimensional space, preserving the original order as well. It simulates the self-organizing feature map’s function of the human cerebrum. SOM is a two-layer neural network that consists of an input layer in a line and an output layer constructed of neurons in a two-dimensional grid as shown in Fig. 3.

The arithmetic of SOM maps random dimension input vectors to one or two-dimension dispersed graphics and maintain its original topologies. With continuous competitive learning, weight vectors would separate from each other in the input space and form one kind of pattern representation. So, SOM learns to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors.

Different from other clustering mapping methods for unsupervised data, mapping relationship of SOM can be highly nonlinear, directly showing the similar input vectors in the source space by points close in the two-dimensional target space [8]. Along with the similarity of the input data, SOM potentially leads to a classification result. Through the approach, SOM has
been applied for PD pattern recognition of turbo-generators [8] and gas insulated switchgear [9].

**SOM-based PD Pattern Recognizing Procedure**

The proposed SOM-based PD pattern recognition scheme for CRCTs has been successfully implemented in PC-based software (MATLAB). The procedures of proposed recognition scheme can be described briefly as follows:

**Step 1** A grid of SOM output layer neurons is set up with initial weight vectors given.

**Step 2** An input vector is chosen randomly from the input space.

**Step 3** An input vector is chosen randomly from the input space.

**Step 4** A winning neuron on output layer is determined by calculating the Euclidean distance between the input vector and the weight vectors of all neurons in the grid. The weight vector of the winner as well as

**Step 5** The weight vectors of its neighboring neurons are adjusted according to learning rate.

**Step 6** Iterate the procedures from Step 2 to 4 above, till the training process is finished.

**Step 7** Save the weight vectors of the trained SOM. Use the trained SOM to identify the defect types of electrical apparatuses.

**EXPERIMENTAL RESULTS**

To verify the proposed approach, a practical experiment was conducted to demonstrate the effectiveness of the PD pattern recognition scheme. The proposed method has been implemented according to the field-test PD patterns collected from the laboratory. Five types of experimental models with artificial defect are purposely manufactured to produce five common PD activities on insulators.

Five PD activities include (1) normal PD activity (NM) in standard epoxy resin insulator, (2) internal cavity discharge (VD) caused by the air cavity inside epoxy resin insulator, (3) internal discharge (MD) caused by a metal-line impurity inside epoxy resin insulator, (4) external discharge in air (ED) between two plane electrodes, (5) corona discharge in air (CD) between a needle electrode and a plane electrode.

Fig. 4 shows the insulator model for NM, VD, and MD, the distance between two plane electrodes is fixed at 10mm. The epoxy resin insulator is normal for NM, with air cavities for VD, and with metal-line impurities for MD. Fig. 5 shows the model for ED, the distance between two plane electrodes is also fixed at 10mm. Fig. 6 shows the model for CD, the distance between the needle tip and the plane electrode is also fixed at 10mm.

The proposed method has been implemented according to the field-test PD patterns collected from our laboratory. The input data to a PD recognition system are the 3-dimension patterns of PD. Associated with their real defect types, there are a total of 250 sample data for different PD events. Each PD event contains 50 patterns of sample data, of which 30 patterns are training data and 20 patterns are testing data.

The NLPCA feature extraction methods were used to extract 12 significant features for each pattern. Based on the feature extracted, the SOM network is further employed for the PD pattern recognition. The number of neurons in input layer of SOM is designed to comprise the 12 significant features mentioned above. The output layer of SOM in three systems is a two-dimensional space comprising 15 by 15 neurons. The training data consist of 150 patterns, which were randomly chosen from the 250 sets of sample data. The other 100 patterns were used as the testing data. After training process, the weight vectors of the trained SOM were saved.
To verify the training effectiveness of the SOM, training data are applied to the SOM again. Table 1 shows the test results of the training data. The proposed method has 100% accuracy for the 150 training feature vectors as shown in Table 1. Table 2 demonstrates the promising performance when 100 testing patterns of three systems were tested. It is shown in Table 2 that among the 100 testing patterns, there are only 7 errors of recognition, two for VD, one for MD, two for ED, and two for CD defects. The average accuracy rate of 100 testing patterns is 93%.

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<tr>
<th>Pattern</th>
<th>Defects Types</th>
<th>Accuracy Rate</th>
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<tbody>
<tr>
<td>Training Data (Total 150 Patterns)</td>
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<tr>
<td>NM</td>
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<td>CD</td>
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<tr>
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<tr>
<td>Testing Data (Total 100 Patterns)</td>
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<td>NM</td>
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<td>MD</td>
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<td>CD</td>
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**CONCLUSIONS**

This paper has proposed an SOM based pattern recognition technique for PD of electrical apparatuses. To verify the effectiveness of the proposed technique, results obtained from experiments were used in this paper. It has been shown that through the features extraction procedure, the extracted statistical featuring operators can significantly reduce the size of the PD pattern database. Also, the SOM based PD pattern recognition scheme is very effective for clustering the defects of electrical apparatuses. To further improve the recognition accuracy of proposed approach, the selection scheme for best combination of feature vector will be investigated for the electrical apparatuses and other high voltage electrical apparatus based on the SOM based PD pattern recognition.

**REFERENCES**


