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# New Attempts in Automated Partial Discharge Identification Using Pulse Sequence Analysis

Hasan Reza Mirzaei[1*], Asghar Akbari[1], Mahdi Allahbakhshi[1], and Mohammead Kharezi[2]
1 K. N. Toosi University of Technology, Faculty of Electrical Engineering
2 Iran-Transfo Company
*E-mail: hr_mirzaei@ee.kntu.ac.ir

**Abstract:** Measuring partial discharge and interpreting its patterns has become a common tool to recognize the type of insulation defects of high voltage equipments. Using statistical features of phase dependent patterns have the most use in PD analysis now. However, these patterns contain less information of PD pulses sequence which is in close relation with defect type. Therefore, nowadays more research studies are conducted in utilizing pulse sequence analysis (PSA) in PD classification. In this literature, a new automated PD classifier based on PSA is introduced and its application is investigated using experimental works on artificial PD defects.

**Keywords:** Partial Discharge, Defect Identification, Pulse Sequence Analysis.

## INTRODUCTION

The nondestructive characteristics of PD measurement and its ability to detect various defects, make it a common test in assessing insulation condition of HV equipments. Nowadays, many attempts have been done to improve PD analysis and its interpretations. Using statistical moments extracted from phase dependent patterns, get the most use in this framework now [1]. However, PD analysis based on these patterns that are created with accumulated discharge data hardly allow a meaningful interpretation of discharge phenomena [2-4]. Therefore, it is needed to seek for new methods with more confidence factor.

Recently some efforts have done to use the sequence of PD pulses in defect classification and some patterns are introduced in this context [2-4]. The main idea of these patterns is on dependency of occurring time of each PD pulse to previous ones. One of the most important patterns of this type is $\Delta u_n$-$\Delta u_{n-1}$, which is created using instantaneous voltage differences of consecutive pulses. In this paper, a new method for automation of PD classification based on $\Delta u_n$-$\Delta u_{n-1}$ pattern is introduced. To investigate the efficiency of this new method, some experiments have done on artificial defects. The results show that newly proposed method is very useful for defect identification.

### Principles

It is known that PD pulses are not independent events. The space charges which remain after each pulse in PD source location modify its electric field and so affect the delay time between consecutive pulses. So it seems that pulse sequence analysis of PD would result in reliable interpretation of defects. The most effective patterns used in PSA, are based on instantaneous voltage differences of consecutive pulses.

In [2, 4], $\Delta u_n$-$\Delta u_{n-1}$ pattern is developed using differences of consecutive pulses instantaneous voltages. In this pattern each PD pulse will be shown with a point. The horizontal axis of $\Delta u_n$-$\Delta u_{n-1}$ pattern represents the current PD pulse $\Delta u$ while vertical axis represents previous pulse $\Delta u$. The $\Delta u_n$ –$\Delta u_{n-1}$ patterns of three different types of PD defects including corona, surface and void discharge defects are shown in Fig. 1.

### Extracting useful features

PD classification is performed by comparing the patterns or the extracted features of unknown type defects with known defects. For this purpose, at first the number of points in two $\Delta u_n$-$\Delta u_{n-1}$ patterns which are going to be compared must be reduced to decrease the needed time. This task must be done so that their important properties of these patterns, including the number of clusters, their location and relative densities, not to be influenced. For this purpose we use a competitive two layer neural network (NN) which structure is shown in Fig. 2. Due to the dimension of input vectors which represent the points in $\Delta u_n$-$\Delta u_{n-1}$ pattern, two neurons in input layers are considered. Therefore a two dimension weight vector will be assigned to each neuron in competitive layer. Also to prevent creation of dead neurons in training phase which sometimes occur in competitive networks, a bias term is added to all of competitive neurons. The task of neurons in competitive layer is to learn the key properties of $\Delta u_n$-$\Delta u_{n-1}$ patterns that are clusters number, their physical position and densities. Hence the sufficient number of neurons in competition layer is required to learn the characteristic properties of these patterns. Meanwhile increasing the number of neurons, increase the time required for learning and comparison. Therefore a trade off must be done using try and error method. Here, we find that twenty competitive neurons will be a suitable choice.

Before training network, the weight vectors of competitive neurons are randomly selected between 0.1 and -0.1 and their bias terms are set to zero. In training phase which is unsupervised, the $\Delta u$ vector of PD pulses are applied to network in a random order. The

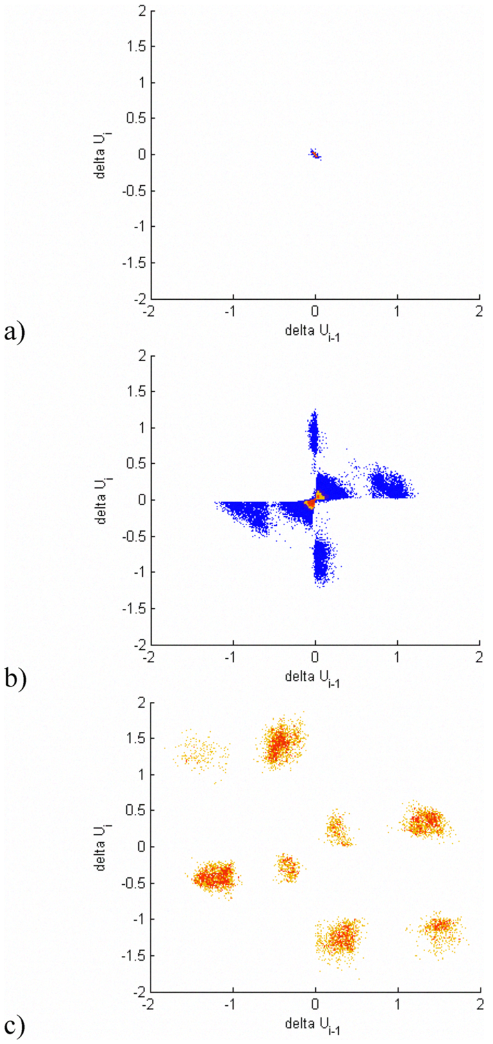


Figure 1. The $\Delta u_n$-$\Delta u_{n-1}$ patterns of artificial PD defects, a) Corona discharge, b) Surface discharge, and c) Void discharge.

distance between input vector and weight vectors competitive neurons will be calculated as follows:

$$d_j = \sqrt{(\Delta u_i - w_{j1})^2 + (\Delta u_{i-1} - w_{j2})^2 + b_j} \quad (1)$$

Where $[\Delta u_i \ \Delta u_{i-1}]$ is the input vector of $i$-th PD pulse voltage difference, $[w_{j1} \ w_{j2}]$ is the weight vector of $j$-th neuron in competitive layer and $b_j$ is its bias. The neuron with minimum distance (more similarity to input) will win competition and will adjust its weight vector closer to input according to kohonen rule and its bias will be increased:

$$\begin{cases} w_{k1}(new) = w_{k1}(old) + \alpha(\Delta u_i - w_{k1}(old)) \\ w_{k2}(new) = w_{k2}(old) + \alpha(\Delta u_{i-1} - w_{k2}(old)) \end{cases} \quad (2)$$

$$b_k(new) = b_k(old) + \beta \quad (3)$$

Where $k$, is the index of winning neuron, $\alpha$ is learning rate and $\beta$ is the growth rate of winner neuron bias. In the end of training, the key parameters of $\Delta u_n$-$\Delta u_{n-1}$ pattern would be extracted by reducing the number of its points. In other words, after training the NN the

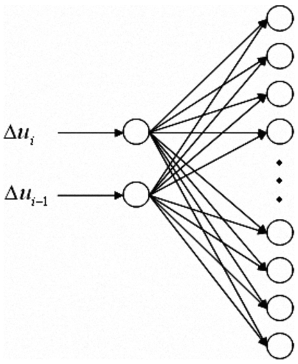


Figure 2. The structure of competitive NN used for feature extraction.

$\Delta u_n$-$\Delta u_{n-1}$ pattern will be reduced to set of neurons weights including twenty 2D vectors. In Fig. 3 the weight vectors of competitive NN, trained by $\Delta u_n$-$\Delta u_{n-1}$ patterns of Fig. 1, are depicted. As it is clear, all clusters of each pattern are recognized by neurons and the number of neurons assigned to each cluster is proportional to their relative densities.

**Comparing $\Delta u_n$ - $\Delta u_{n-1}$ patterns**

Two $\Delta u_n$-$\Delta u_{n-1}$ patterns could be compared by

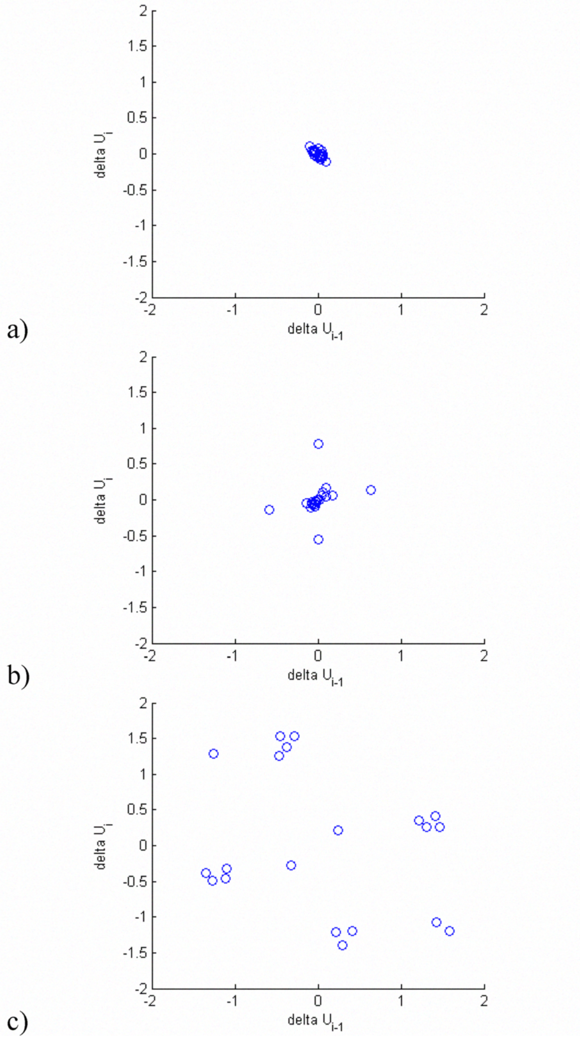


Figure 3. The key properties of Fig. 1 patterns extracted by NN.

calculating Euclidian distance between their extracted sets of vectors:

$$d = \sum_{j=1}^{20} \sqrt{(w_{j1} - W_{j1})^2 + (w_{j2} - W_{j2})^2}\,, 1 \le j \le 20 \quad (4)$$

Where $w$ and $W$ are vectors sets of two patterns. In such a way, if two patterns belong to a same class, because of their similarity in the number of clusters, their location and relative densities and therefore their similar vectors sets, the calculated distance will be low while the calculated distance for PDs with different classes will be high. But the problem with equation (6) is the order of vectors in two sets that are compared. Using this equation the vectors of two sets will be compared in the order of their indexes, but not by the order of their vectors location in $\Delta u_n$-$\Delta u_{n-1}$ pattern. So, the distance of two patterns with same classes would be high.

To explain the case, suppose that we want to compare a new surface discharge activity, which it's original and reduced $\Delta u_n$-$\Delta u_{n-1}$ patterns are shown in Fig. 4a and 4b, by a surface discharge pattern shown in Fig. 2b and 3b. Since both PDs have same defect types, their $\Delta u_n$-$\Delta u_{n-1}$ patterns own clusters with similar locations and relative densities, and therefore low distance between their vectors sets is prospected. But if the equation (6) is used in its raw form, vectors with same indices that represent dissimilar clusters of both patterns would be compared. This problem is caused by random selecting of NN weights before training and random presenting of $\Delta u$ vectors during training phase. In Fig. 4c, the vectors of Fig. 4b which are depicted by circles are compared using equation (6) with vectors of Fig. 3b shown by triangles. The vectors of two sets compared with each other are linked with a line. However the right comparison which is expected is shown in Fig. 4d. So it is necessary to make some changes in equation (6).

To solve this problem, we apply genetic algorithm (GA) to find the right order of vectors indices to be compared. Due to the number of vectors in vector set, each chromosome consists of twenty genes:

$$Chr = [p_1, p_2, p_3, \ldots, p_{20}], \quad p_i \ne p_j$$
$$1 \le p_i \le 20\,, p_i \in \mathrm{N} \qquad (5)$$

Integer numbers between 1 and 20 randomly assigned to genes of each chromosome of initial population. In this order, the value of gene $p_i$ indicates the vector index of second vectors set to be compared by $i$-th vector of the first vectors set. The cost function which must decreased during optimization, is considered the distance between two vectors sets with the order suggested by each chromosome:

$$Cost\,(Chr) = \sum_{j=1}^{20} \sqrt{(w_{j1} - W_{p_j1})^2 + (w_{j2} - W_{p_j2})^2} \quad (6)$$

Minimizing this cost function will suggest the order of comparing between vectors of two sets that minimizes the distance. In such a way, if two vectors sets belong to a same defect, the cost function would lead to a chromosome providing the order in which similar clusters will be compared and hence the calculated

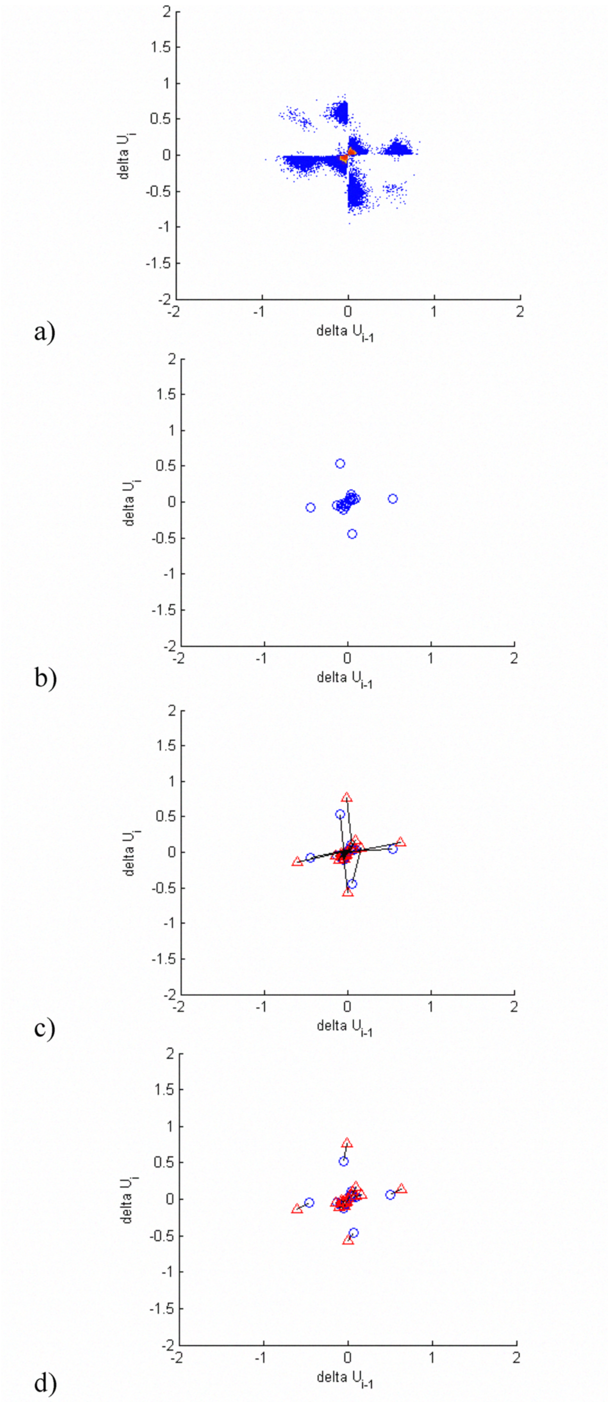


Figure 4. a) The $\Delta u_n$-$\Delta u_{n-1}$ pattern of another surface discharge and b) its reduced pattern, c) incorrect and d) correct comparing vectors sets of new surface discharge (○) with surface discharge shown in Fig. 5b (Δ) using equation (6).

distance will be low, but if the defects are not the same the calculated distance even with the best chromosome would be high, because their $\Delta u_n$-$\Delta u_{n-1}$ patterns do not have similar clusters.

In Fig. 5 vectors set of surface discharge shown in Fig. 4b and vectors sets of Fig. 3a, 3b and 3c are compared using suggested GA. The lines in these figures indicate the couples of vectors which are compared with each other. The calculated distances in Fig. 5a, 5b and 5c are 2.45, 1.22 and 24.03 respectively. Thus as illustrated it becomes clear that using suggested genetic algorithm, the distance of vectors sets with same defect types will be more lower than distance between vectors sets with different types.

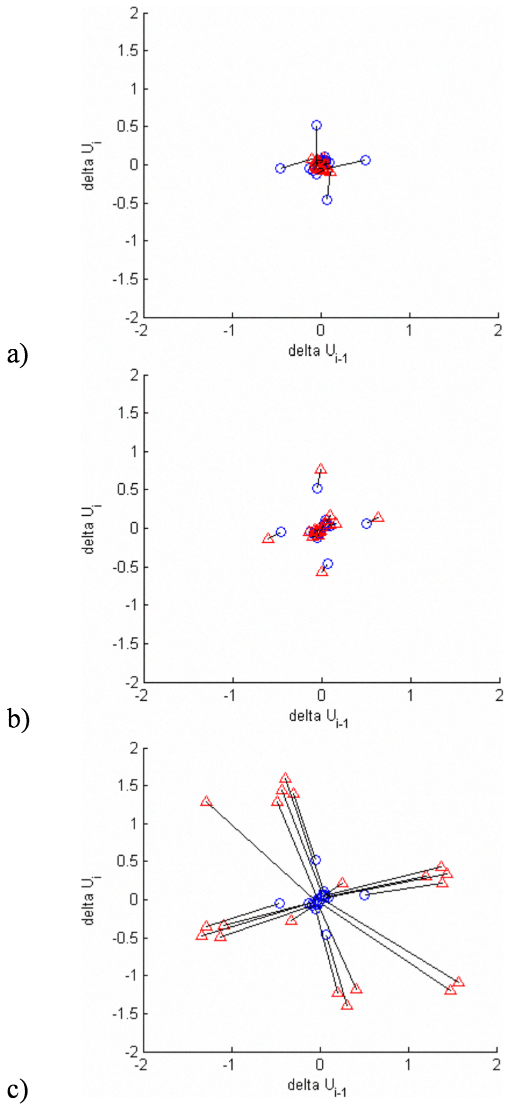


Figure 5. Comparing Fig. 4b pattern (○) with a) Fig. 3a pattern (Δ), b) Fig. 3b pattern (Δ), and c) Fig. 3c pattern (Δ).

### Classification Results

To inquire the applicability of proposed method, some experiments have done on artificial PD defects. Then with the help of the database patterns of a conventional PD measuring system and using new method, the experienced PD activities were classified. The results which are shown in Table 1, indicate that new automated PD classification method is successful in identifying PD defects types.

### Conclusion

The space charges in PD source location affect the sequence of pulses. With the help of PSA, these effects could be used in defect identification. For this purpose a new method was proposed to automate the procedure of PD defect identification which uses $\Delta u_n$-$\Delta u_{n-1}$

**Table 1.** The percentage of correct estimation of PD defect type by new proposed method.

| **DEFECT TYPE** | Corona | Surface Discharge | Void Discharge |
|---|---|---|---|
| Number of patterns | 6 | 5 | 4 |
| Percentage of correct classification | %100 | %100% | %80 |

patterns. The classification results of this new method on artificial defects show very satisfactory results.

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