IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676,p-ISSN: 2320-3331, Volume 6, Issue 5 (Jul. - Aug. 2013), PP 50-57
www.iosrjournals.org

Investigation on Using Fractal Geometry for Classification of Partial Discharge Patterns

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Abstract : *Classification of Partial discharge (PD) patterns is an important tool to determine the sources of the PD. Also the features that specify of the patterns can be used monitor the condition of the electrical insulation. A PD patterns classification approach of artificial partial discharge sources by using neural networks is proposed in this paper. The classification process was based on features generated from three-dimension PD patterns. These features were obtained with the aid of fractal geometry. The box counting technique is used to generate the fractal features (fractal dimension and lacunarity). Each PD pattern has a unique Fractal dimension and several values for lacunarity depends upon the size of the box. Therefore each PD pattern is characterized by two features but with several quantities. The number of input features and their contents of information determine the performance of neural networks based classification system. In this paper an attempt to improve the performance of PD classification systems by minimizing the number of the input features was introduced. This was done by investigating the ability the different lacunarity values to classify different PD sources. A wide range of box size was investigated. The obtained results show that the lacunarity values generated from a very narrow range of box sizes has the maximum ability for PD classification.*
***Keywords**: Partial Discharge Pattern, Fractal Dimension, Lacunarity*

I. INTRODUCTION

Partial discharge is a natural phenomenon occurring in electrical insulation systems (an electrical discharge that doesn't completely bridge the distance between two electrodes under high voltage stress), which invariably contain tiny defects. Partial discharge is considered the commencement of failure of insulation of electrical devices which deteriorates due to thermal, mechanical, electrical and environmental stresses [1].

Although the magnitude of such discharges is usually small, it cause progressive deterioration, ageing of insulation and may lead to ultimate failure of electrical equipment [2]. If such discharge is not detected then fault may increase and eventually leads to the catastrophic failure in the power system equipment. The occurrence of imperfections in the insulation system of a power apparatus such as voids, cavities due to the formation of cracks and surface in-homogeneities is unavoidable in electrical insulation system of any power apparatus and gives rise to a large variety of physical phenomena leading to partial discharges (PD) and emission of several signals (i.e. electrical signal, acoustic pulses and chemical reactions) is associated when partial discharge occurs in the insulation material.

The measurement of partial discharge (PD) activity has become an invaluable tool for monitoring insulation condition of high-voltage components in service since it is important for power utilities to obtain an indication of the time for its degradation and subsequent breakdown.

The automated recognition of PD patterns has been widely studied recently. Various pattern recognition techniques have been proposed, including expert systems [3], statistical parameters [4], fuzzy clustering [5], extension theory [6], PD-fingerprints [7], and neural networks (NNs) [8, 9]. The expert system and fuzzy approaches require human expertise, and have been successfully applied to this field.

Recently, fractal features were employed for discharge recognition with encouraging results [10]. In fractal method, the fractal dimension and lacunarity, will be calculated from PD patterns. There are many reasons to use fractal features, details of computing fractal dimension and lacunarity from 3-D partial discharge patterns have already been published in [11]. Fractal has been very successfully used in description of naturally occurring phenomena and complex shape, such as mountain ranges, coastlines, clouds, and so on, wherein traditional mathematical were found to be inadequate [12, 13]. This complex nature of the PD pattern shapes and the ability of fractal geometry to model complex shapes have encouraged many authors to investigate the feasibility of fractal dimension for PD pattern interpretation.

The aim of this work is to examine further the discriminating abilities of the fractal features when a wide variety of discharge patterns, have to be recognized. And by using a conventional phase resolved PD analyzer, 3-d PD patterns corresponding to different PD sources were acquired. These PD sources are due to the artificially introduced defects within carefully designed insulation models such as internal void discharge in cable. This work will give a more complete picture about this technique of partial discharge patterns recognition.

II. PRACTICAL PD FIELD MEASUREMENT

PD measurement and identification can be used as a good insulation diagnosis tool to optimize both maintenance and life-risk management for power apparatuses. The IEC60270 [14] establishes an integral quality assurance system for PD measurement instead of the old standard IEC60060-2. It ensures accuracy of measuring results, comparability and consistency of different instruments and measuring methods. Moreover, the IEC60270 provides digital PD measuring recommendations as well as the analog measuring. In this work, all PD experiments are based on IEC60270.

Figures 1 and 2 show the PD experiment laboratory, including a set of precious instrument has been used. It consists of a PD analyzer (the computer aided measuring system LDD-6), a high-voltage control panel, a high-voltage transformer, a calibration capacitor, a coupling capacitor and specimen of high voltage cable as a test object.

Fig. 1: Practical PD field measurement

Fig. 2: Test arrangement

III. EXTRACTION OF PD FEATURES FOR RECOGNITION PURPOSES

In recent years, more attention are directed to the fractal technique for classification of textures, objects present in images, natural scenes and for modeling complex physical processes. Fractal dimensions are allowed to depict surface asperity of complicated geometric things. Therefore, it is possible to study complex objects with simplified formulas and fewer parameters [15]. The fractal features, fractal dimension and lacunarity of phase windows are extracted to highlight the more detailed characteristics of the raw 3D PD patterns.

1. Fractal Dimension (FD)

Different methods have been proposed to estimate the FD [16, 17]. While the definition of fractal dimension by self-similarity is straightforward, it is often difficult to compute for a given image data. However, the box counting technique can be used for this purpose easily. In this work, the method suggested by Keller

[18] for the computation of fractal dimension from an image data has been followed. Let p(m, L) define the probability that there are m points within a box of size L (i.e. cube of side L), which is centered about a point on the image surface. P(m, L) is normalized, as below, for all L [6].

$$\sum_{m=1}^{N} p(m.L) = 1 \tag{1}$$

Where, N is the number of possible points within the box. Let S be the number of image points (i.e. pixels in an image). If one overlay the image with boxes of side L, then the number of boxes with m points inside the box is (S/m) p(m, L). Therefore, the expected total number of boxes needed to cover the whole image is

$$N(L) = \sum_{m=1}^{N} \frac{S}{m} p(m.L) = S \sum_{m=1}^{N} \frac{1}{m} p(m.L) \tag{2}$$

The fractal dimension can be estimated by calculating p(m, L) and N(L) for various values of L, and by doing a least square fit on [log(L), -log(N(L))]. To estimate p(m, L), one must center the cube of size L around an image point and count the number of neighboring points m, that fall within the cube. Accumulating the occurrences of each number of neighboring points over the image gives the frequency of occurrence of m. This is normalized to obtain p(m,L). Values of L are chosen to be odd to simplify the centering process. Also, the centering and counting activity is restricted to pixels having all their neighbors inside the image. This will obviously leave out image portions of width = (L −1) / 2 on the borders. This reduced image is then considered for the counting process. As it seen, large value of L results in increased image areas from being excluded during the counting process, thereby increasing uncertainty about counts near border areas of the image. This is one of the sources of errors for the estimation of p(m, L) and thereby FD. Additionally, the computation time grows with L value.

2. Lacunarity

Theoretically, ideal fractal could confirm to statistical similarity for all scales. In other words, fractal dimensions are independent of scales. However, it has been observed that fractal dimension alone is insufficient for purposes of discrimination, since two differently appearing surfaces could have the same value of FD. To overcome this, Mandelbrot [19] introduced the term called lacunarity Λ, which quantifies the denseness of an image surface. Many definitions of this term have been proposed and the basic idea in all these is to quantify the 'gaps or lacunae' present in a given surface. As a result, lacunarity can be thought as a measure of 'gappiness' of a geometric structure. More precise definition was given as a measure for the deviation of a geometric object from translational invariance [20, 21]. The concept of lacunarity was established and developed from the scientific need to analyze multi-scaling texture patterns in nature (mainly in medical and biological research), as a possibility to associate spatial patterns to several related diagnosis. Regarding texture analysis of urban spaces registered by satellite images, lacunarity is a powerful analytical tool as it is a multi-scalar measure, that is to say, it permits an analysis of density, packing or dispersion through scales. In the end, it is a measure of spatial heterogeneity, directly related to scale, density, emptiness and variance. It can also indicate the level of permeability in a geometrical structure [22]. One of the useful definitions of this term as suggested by Mandelbrot is

$$M(L) = \sum_{m=1}^{N} mp(m.L) \tag{3}$$

$$M^2(L) = \sum_{m=1}^{N} m^2 p(m.L) \tag{4}$$

Where N is the numbers of point in the data set of size L, the lacunarity becomes

$$\Lambda(L) = \frac{M^2(L) - [M(L)]^2}{[M(L)]^2} \tag{5}$$

Figure 3 shows the overall procedure for extracting fractal features. The first step is to transfer PD pattern to a 360×360 matrix and use boxes with different sizes to cover the matrix. In fractal dimension computation, we can obtain N (L). In lacunarity computation, M (L) and M2 (L) have to be calculated and then by using equation (5) lacunarity can be determined.

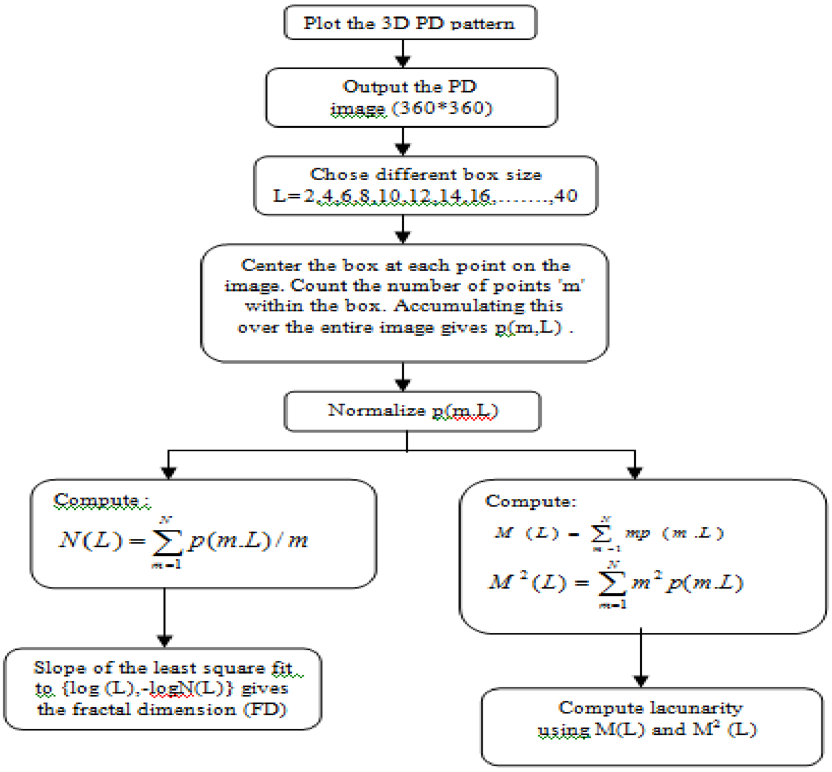

Fig.3 Procedure for computing fractal dimension and lacunarity

IV. APPLICATION OF PRACTICAL PARTIAL DISCHARGE SOURCE

In this case the sample of high voltage cable is used, where this sample was used for generating of partial discharge sources as shown in Figure 2. Three types of partial discharge generation source, including no defect (health case), internal discharge (1 void) and internal discharge (2 voids) were used, respectively.

Partial discharge signal was measured by using partial discharge detector (the computer aided measuring system LDD-6). 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. Typical measurement results of each partial discharge generation source are illustrated in Figures 4, 5 and 6 respectively.

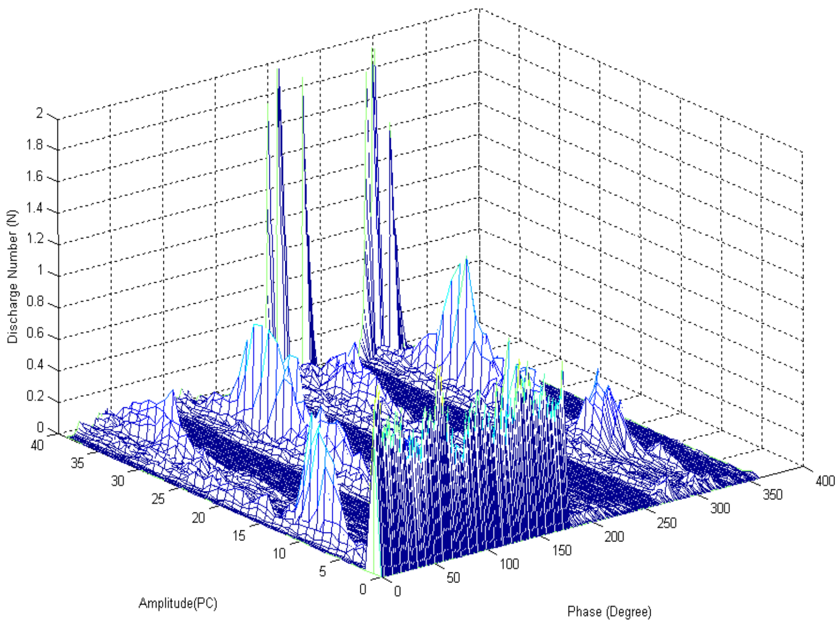

Fig. 4: Partial discharge pattern due to health case

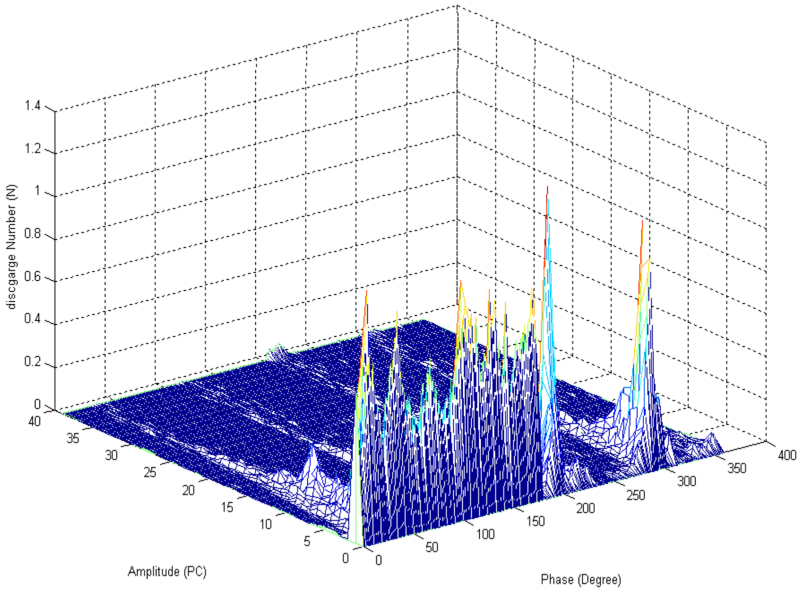

Fig. 5: Partial discharge pattern due to internal discharge (1 void)

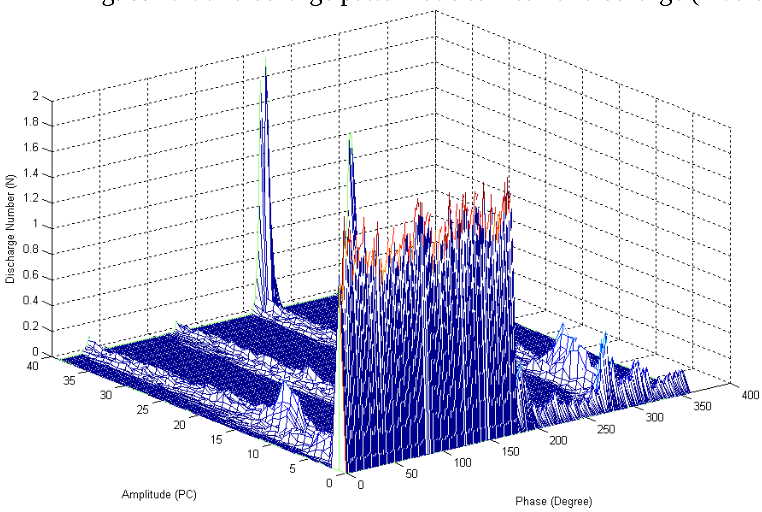

Fig. 6: Partial discharge pattern due to internal discharge (2 voids)

Figure 7 is a simple plot of the set [log(L), -log(N(L))] for the different values of L (computed for all patterns). A least square fit to this dataset is performed to obtain the fractal dimension D.

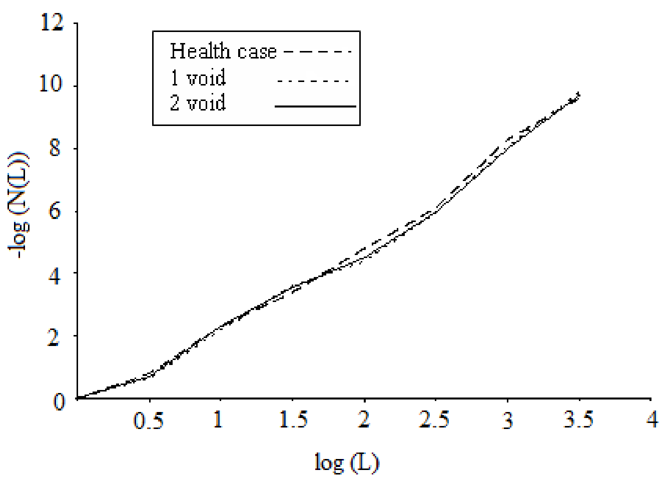

Fig. 7: The sample plot of the set [log (L), - log (N (L))] for different patterns

The corresponding lacunarity is also computed for each value of L. Figure 8 shows its variation with respect to L.

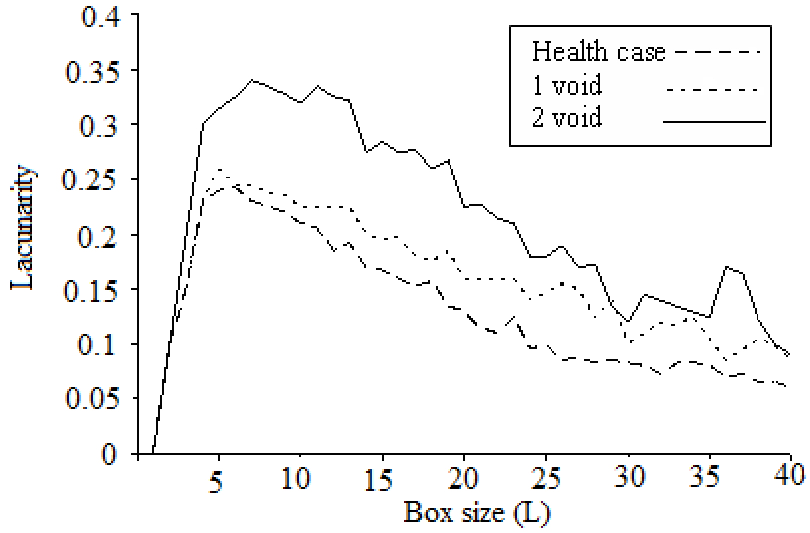

Fig. 8: The sample plot of the variation of lacunarity with respect to box size L

Fractal features are computed for all the available patterns recorded. Figure 9 is a plot of fractal dimension and lacunarity for different discharge sources. It is obvious that patterns belonging to a particular defect type gather together.

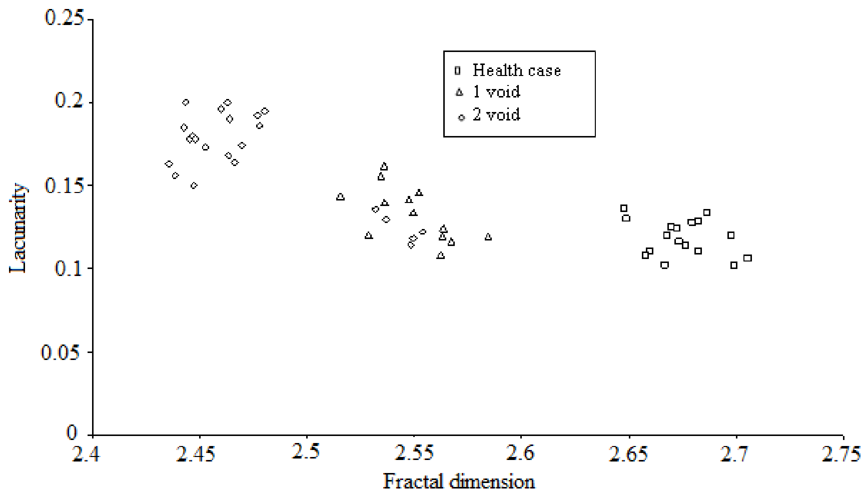

Fig. 9: Fractal dimension and lacunarity of different discharge sources

Obviously, differences in pattern of partial discharge measurement results were obtained. Each partial discharge generation source generated individual partial discharge pattern. Then, these measurement data are used to test the purposed technique. Characteristics of partial discharge data were calculated by using fractal features to apply for pattern recognition and classification. Characteristics of health case, characteristics of internal discharge (1 void) and characteristics of internal discharge (2 voids) are shown in Tables 1, 2 and 3, respectively. These results were used for pattern recognition and classification.

Table 1: characteristic of health case

No. of pattern	1	2	3	4	5	6	7	8	9	10
Fractal dimension	2.705	2.699	2.682	2.672	2.676	2.667	2.648	2.625	2.625	2.610
Lacunarity	0.106	0.102	0.11	0.124	0.114	0.12	0.13	0.128	0.129	0.12

Table 2:

No. of pattern	1	2	3	4	5	6	7	8	9	10
Fractal dimension	2.5285	2.5625	2.5152	2.5633	2.5497	2.5844	2.554	2.5495	2.5157	2.5496
Lacunarity	0.12	0.108	0.156	0.119	0.118	0.119	0.122	0.119	0.144	0.134

characteristic of internal discharge (1 void)

Table 3: characteristic of internal discharge (2 voids)

No. of pattern	1	2	3	4	5	6	7	8	9	10
Fractal dimension	2.493	2.4144	2.4906	2.493	2.4385	2.416	2.4084	2.4472	2.4803	2.4778
Lacunarity	0.2	0.196	0.178	0.2	0.156	0.185	0.144	0.15	0.195	0.186

V. RECOGNITION RESULTS AND DISCUSSION

The problem in this work is how to classify the type of defect that produced those PD data. 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. The NN-based PD classification system randomly chooses 20 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. Figure 10 shows the classified results of the proposed system with different input patterns.

It is obvious that the ability of NN-based PD classification system depends upon the length of the box side. The classification accuracy starts to increase with increasing the box size that has been used to determine the lacunarity. The classification accuracy reaches maximum at L = 8 and then started to decrease. This result emphasizes that the using of large value of L will increase the computation time without any improvement to the classification accuracy. Therefore limited values of L can be used to calculate the fractal dimension and lacunarity.

VI. CONCLUSIONS

Identification of partial discharge sources through the analysis of PD patterns are important tool for the diagnosis of insulating materials. For many years ago, several techniques were used to generate features which are able to characterize the different PD sources. These techniques include statistical method, textures algorithms, fractal geometry etc. Calculating the fractal features like the fractal dimension and lacunarity is based on the box counting technique. This technique is applied by covering the three-dimension PD pattern with boxes of different sizes. This application of boxes results in a single value for fractal dimension and several values for lacunarity. The classification time is directly proportional to the number of input features. Therefore this paper is an attempt to minimize the number of input features through the determining the box size which gives the lacunarity value its maximum discrimination power for different PD sources. A NN-based PD pattern classification method was used for this purpose. The obtained results show that a combination of fractal dimension and a single value of lacunarity are sufficient to discriminate between different PD sources. This single value must be calculated for a given box size. Classification accuracy increases with increasing the box size to certain length and then starts to decrease. It is important to note that the value of box size which gives the lacunarity its maximum ability of classification is very small compared to total size of the three-dimension PD pattern.

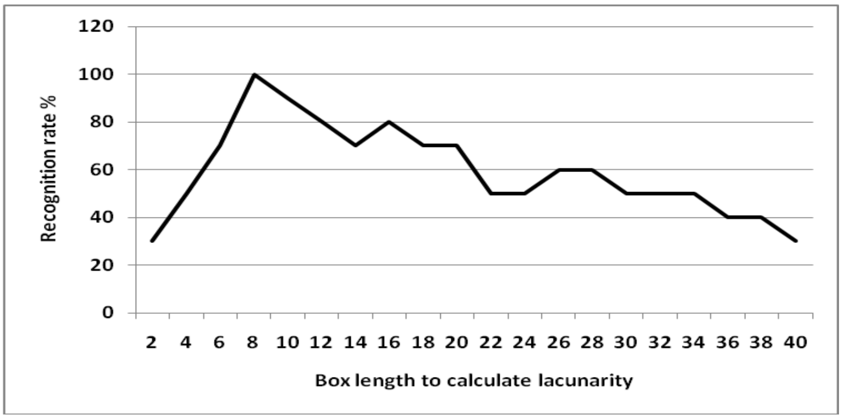

Fig. 10: Accuracy of classification according to different values of lacunarity which have been used in combination with fractal dimension

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