Classification Of Partial Discharge Patterns Using Fractal Geometry

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ABSTRACT

Partial discharge (PD) pattern recognition is an important diagnostic tool to get the dielectric deterioration degree of electrical insulation. A PD pattern recognition approach of artificial partial discharge sources based on neural networks is proposed in this paper. A commercial PD detector is used to measure the three-dimension PD patterns. Two fractal features (fractal dimension and lacunarity) were extracted from the raw PD patterns. The box counting technique is used to generate the fractal features. Fractal dimension is a constant value for each pattern. On the other hand, each pattern has several values for lacunarity depends upon the size of the box. Therefore each PD pattern is characterized by several quantities. The performance of neural networks based recognition system depends upon the number of input features as well as upon their contents of information. This paper is an attempt to improve the performance of PD recognition systems by minimizing number of input features. This can be done through selecting the value of lacunarity which has the maximum ability to classify different PD sources. A wide range of lacunarity values were tested. The obtained results show that a very narrow range of lacunarity values has the maximum ability for PD classification.

Keywords:- Partial Discharge, Fractal Dimension, Lacunarity, and PD Recognition Patterns.

I. INTRODUCTION

PD is electrical discharges that do not completely bridge the distance between two electrodes under high voltage stress. It is small electrical sparks that occur within the electric insulation of electrical equipment. 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 [1]. Occurrence of PD in electrical insulation is always associated with emission of several signals (i.e. electrical signal, acoustic pulses and chemical reactions). The main purpose of insulation diagnosis for power apparatus is to give system operators the information on dielectric deterioration degree of HV equipment. There is a recognized need for condition monitoring and automated diagnostic systems in the electrical utilities. Such systems provide the ability to identify defects as they occur, allowing the scheduling of maintenance, avoidance of equipment failure, optimizing the operation of the equipment and increasing reliability. Automated diagnostic systems can only be successful if there exists a way of capturing information that indicates the health of the apparatus. Analysis of PD data provides one such indication [2]. Commercial PD detectors can measure the electrical signal of electrical field variety in defect model, and an experienced expert can use the PD patterns to identify the defect types in the tested object. The main parameters of the 3D PD patterns are phase angle φ, discharge magnitude q, and the numbers of discharge n. 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[3, 4]. PD also is a natural phenomenon occurring in electrical insulation systems, which invariably contain tiny defects and non-uniformities, and gives rise to a variety of complex shapes and surfaces, both in a physical sense as well as in the shape of PD patterns acquired using digital PD detector. 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 automated recognition of PD patterns has been widely studied recently. Various pattern recognition techniques have been proposed, including expert systems [5], statistical parameters [6], fuzzy clustering [7], extension theory [8], PD-fingerprints [9], and neural networks (NNs) [10, 11]. 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 [12]; 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, two fractal features that extract relevant characteristics from the raw 3-D PD patterns are presented for the proposed NN-based classifier. It 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, 30 sets of PD patterns from HV defect models are tested.

II. PRACTICAL PD FIELD MEASUREMENT

When the intensity of electric field exceeds the breakdown threshold value of a defective dielectric, PD occurs and results in a partial breakdown in the surrounding dielectrics. PD is a symptom of insulation deterioration. Therefore, 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 new standard IEC60270 [13] for PD measurement has been published in 2001, which establishes an integral quality assurance system for PD measurement instead of the old standard IEC60060-2 published in 1994. The standard IEC60270 ensures accuracy of measuring results, comparability and consistency of different instruments and measuring methods. Moreover, the new standard provides digital PD measuring recommendations as well as the analog measuring. In this work, all PD experiments are based on the new standard IEC60270.

A PD experiment laboratory, including a set of precious instrument has been used. The constitution of the laboratory includes a PD analyzer (the computer aided measuring system LDD-6), a high-voltage control panel, a high-voltage transformer, a calibration capacitor, and a coupling capacitor.

III. EXTRACTION OF PD FEATURES FOR RECOGNITION PURPOSES

Fractals have been very successfully used to address the problem of modeling and to provide a description of naturally occurring phenomena and shapes, wherein conventional and existing mathematical methods were found to be inadequate. In recent years, this technique has increased attention for classification of textures and objects present in images and 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 [14]. PD also is a natural phenomenon occurring in electrical insulation systems, which invariably contain tiny defects and non-uniformities, and gives rise to a variety of complex shapes and surfaces, both in a physical sense as well as in the shape of 3D PD patterns acquired using digital PD detector. The fractal features, fractal dimension and lacunarity of phase windows are extracted to highlight the more detailed characteristics of the raw 3D PD patterns.

II. A. FRACTAL DIMENSION

The fractal dimension (FD) has been applied in texture analysis and segmentation shape measurement and classification of image and graphic and analysis in other fields. There are quite a few definitions of FD making sense in certain situations. Thus, different methods have been proposed to estimate the FD [15, 16].

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 [17] 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* [8].

$$\sum_{m=1}^{n} p(m.L) = 1 \qquad (1)$$

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

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

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. Hence values from L = 2 to L = 40 were chosen for this work. Figure1 shows a sample plot of *log (L) and −log (N (L))*.

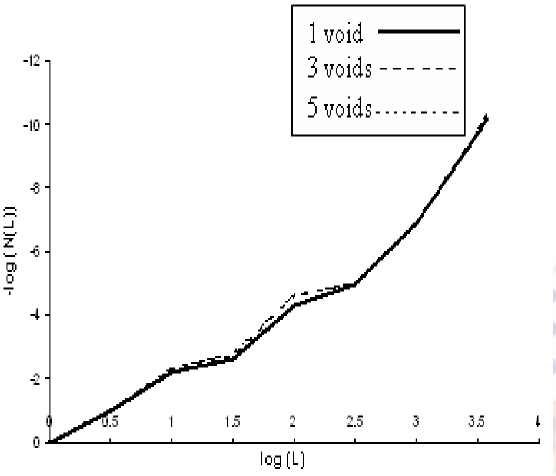

Figure 1: The sample plot of the set [log (L), - log (N (L))] for different box size L

II. B. 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 [18] 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 [19, 20]. 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 [21]. One of the useful definitions of this term as suggested by Mandelbrot is

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

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

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

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

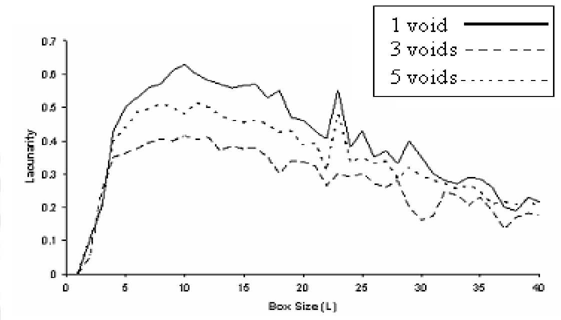

Figure 2: The sample plot of the variation of lacunarity with respect to box size L

Figure2 shows a sample plot of the variation of lacunarity with respect to box size *L* for different PD patterns. Figure3 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 M^2 *(L)* have to be calculated and then by using equation (5) lacunarity can be determined.

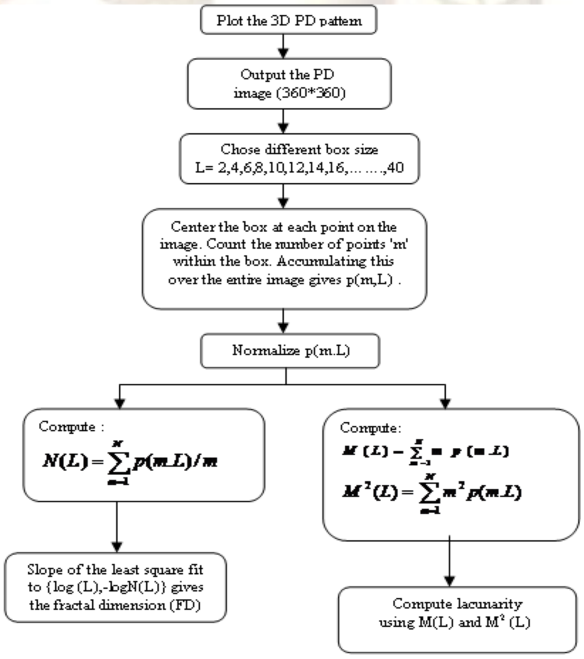

Figure 3: Procedure for computing fractal dimension and lacunarity

IV. PARTIAL DISCHARGE EXPERIMENTAL RESULTS

Using a conventional phase resolved PD analyzer (the computer aided measuring system LDD-6), 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. Three types of partial discharge generation source were used. The internal discharge due to one void, three voids and five voids in mica insulators as shown in Figure 4 were measured. 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 Figure 5, Figure 6, and Figure7.

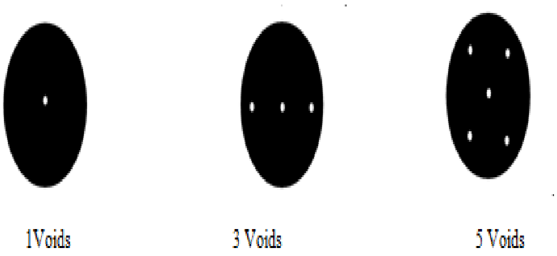

Figure 4: Test samples

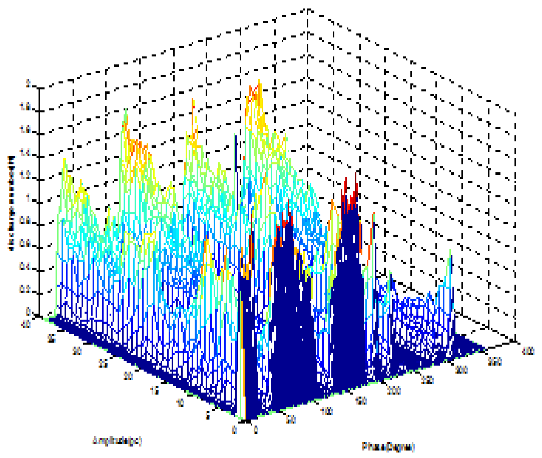

Figure 5: Partial discharge pattern due to one void

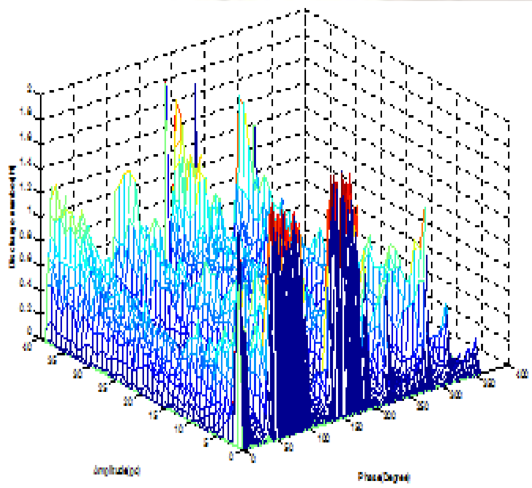

Figure 6: Partial discharge pattern due to three voids

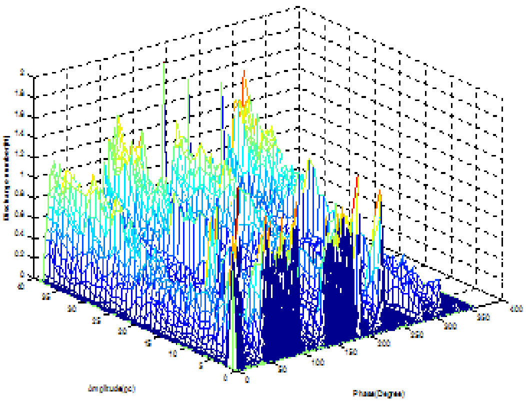

Figure 7: Partial discharge pattern due to five voids

Obviously, differences in patterns of partial discharge measurement results were obtained. Each partial discharge generation source generated individual partial discharge pattern. These measurement data are used to test the purpose technique. Characteristics of partial discharge data were calculated by using fractal features to apply for pattern recognition and classification.

The individual 3-D PD patterns 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). Fractal features are computed for all the available patterns recorded. Figure 8 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.

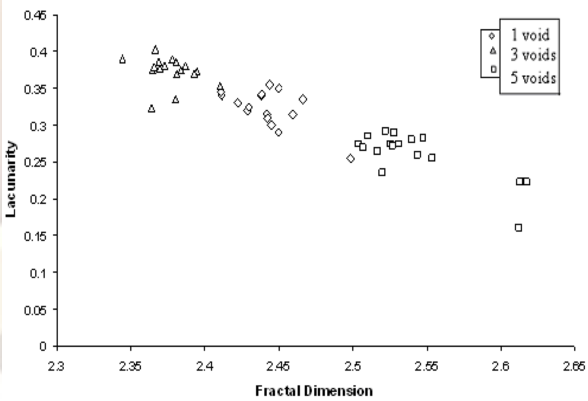

Figure 8. Fractal dimension and lacunarity of different discharge sources

V. RECOGNITION RESULTS AND CLASSIFICATION

The main objective of this paper is how to determine the box size which acquires the lacunarity the maximum ability to classify different types of defect that produce PD data. In this aim, a multilayer artificial NN could appear as a suitable possible solution to classify PD patterns. 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 neuron number of its input is determined by the number of fractal features. The number of neurons in the hidden layer depends on the number of the input data. The neuron number of output layer is determined by the number of defects to be identified, which are three in this study. To demonstrate the recognition ability, 30 sets of PD patterns are used to test the proposed PD recognition system. The NN-based PD recognition system randomly chooses 20 sets from the data as the training data set, and the rest of the sets as testing data. In order to determine the optimum value of lacunarity which has the maximum ability to discriminate between different PD sources, combinations of fractal dimension and lacunarity were used for the training of the neural network. Table I shows the accuracy of classification of the proposed system with the different combinations.

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 = 10 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.

TABLE I Accuracy of Classification According to Different Values of Lacunarity which Have Been Used in Combination with Fractal Dimension

Box length to calculate the lacunarity	Recognition rate (%)
2	30
4	50
6	60
8	80
10	100
12	90
14	70
16	80
18	70
20	60
22	50
24	50
26	60
28	60
30	50
32	40
34	40
36	40
38	40
40	30

VI. CONCLUSIONS

Analysis of PD patterns and identification of discharge sources are important tools for the diagnosis of HV insulation system. Through the last decades, several features including the fractal geometry have been used to characterize the PD patterns. Calculating the fractal features like the fractal dimension and lacunarity depends on the box counting technique. This technique is based on covering the PD pattern with boxes having different sizes. Increasing the box size leads to increasing the computational time. Therefore this paper is an attempt to investigate the effect of box size on the ability of fractal features to discriminate between different PD sources. A NN-based PD pattern recognition method was used for this purpose. The obtained results show that the fractal dimension alone is not sufficient to discriminate between different PD sources. On the other hand, lacunarity is more efficient for this purpose. But the ability of lacunarity depends upon the size of the box which used to calculate the value of lacunarity. 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 acquires the lacunarity its maximum ability of classification is very small compared to total size of the full PD pattern. Based on this result a limited value of box size could be used to generate the fractal features which will reduce the computational time significantly.

REFERENCES

[1] E. Kuffel, W.S. Zaengl and J. Kuffel, “High Voltage Engineering Fundamentals”. 2nd, Butterworth – Heinemann, 2000

[2] S. Rudd, S. D. J. McArthur and M. D. Judd "A Generic Knowledge-based Approach to the Analysis of Partial Discharge Data", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 17, No. 1; February 2010.

[3] Z. Zhao, Y. Qiu, and E. Kuffel, “Application of Fractal to PD Signal Recognition,” IEEE International Symposium on Electrical Insulation, April 2002, pp. 523-526.

[4] L. Jian, T. Ju, S. Caixin, L. Xin, and D. Lin, “Pattern Recognition of Partial Discharge with Fractal Analysis to Characteristic Spectrum,” International Conference on Properties and Application of Dielectric Materials, Vol. 2, June 2000, pp. 21-26.

[5] K. Zalis, “Applications of expert systems in evaluation of data from partial discharge diagnostic measurement,” in Proc. 7th International Conf. Properties and Applications of Dielectric Materials, pp. 331-334, June 2003.

[6] Muhamad Mansor, Prodipto Sankar Ghosh & Ahmad Basri Abdul Ghani ," PD Patterns

Recognition In XLPE Cable Under Various Thermal Conditions Using Statistical Technique ", IJRRAS 5 (2) ,November, (2010),p.p. 171-181.

[7] S. Boonpoke and B. Marungsri" Pattern Recognition of Partial Discharge by Using Simplified Fuzzy ARTMAP", World Academy of Science, Engineering and Technolog China, pp 212-219, September 2010.

[8] Hung-Cheng Chen, Feng-Chang Gu, Chun-Yao Lee "A New Method Based on Extension Theory for Partial Discharge Pattern Recognition", Wseas Transactions on Systwms, Issue 12, Volume 7, pp.1402-1411, December 2008.

[9] PO-Hung Cheni, Hung-Cheng Chen, An Liu, Li-ming Chen "Pattern Recognition For Partial Discharge Diagnosis Of Power Transformer", Proceedings of the Ninth International Conference on Machine Learning and Cybernetics, Qingdao, Vol. 4493, pp. 2996-3001, July 2010.

[10] Hung-Cheng Chen, PO-Hung Chen, and Meng-Hui Wang " Partial Discharge Classification Using Neural Networks and Statistical Parameters", International Conference on Instrumentation, Measurement, Circuits & Systems, April 15-17, 2007,p.p 84-88.

[11] Karthikeyan, B., Gopal, S., & Venkatesh, S. (2006). "ART 2 – An unsupervised neural network for PD pattern recognition and classification", International Journal on Expert Systems with Applications, 31, 345–350.

[12]. Salama, M.M.A., Bartnikas, R.: Determination of Neural Network Topology for Partial Discharge Pulse Pattern Recognition. IEEE Trans. on Neural Networks 13 (2002) 446-456.

[13] IEC, High-Voltage Test Techniques-Partial Discharge Measurements, IEC 60270, 2001.

[14] L. Satish, W. S. Zaeng, “Can Fractal Features Be Used for Recognizing 3-D Partial Discharge Patterns? ” IEEE Transactions on Dielectrics and Electrical Insulation, Vol. 2, June 1995, pp. 352-359.

[15] Jian Li, QianDu, CaixinSun " An improved box-counting method for image fractal dimension estimation", Contents lists available at Science Direct, Pattern Recognition 42 (2009) 2460 – 2469.

[16] B. S. Raghavendra, and D. Narayana Dutt "Computing Fractal Dimension of Signals using Multiresolution Box-counting Method", International Journal of Information and Mathematical Sciences 6:1, p.p 50-65, 2010.

[17] J.M. Keller, S. Chen, R.M. Crownover, Texture description and segmentation through fractal geometry, J. Comput. Vis. Graphics Image Process. 45 (1989) 150–160.

[18] B. B. Mandelbrot, The Fractal Geometry of Nature, New York, Freeman, 1983.

[19] Gefen et al., 1984. Phase transitions on fractals: III infinitely ramified lattices. Journal of Physics A, 17, pp.1277-1289.

[20] Y. Malhi, R.M. Román-Cuesta"Analysis of lacunarity and scales of spatial homogeneity in IKONOS images of Amazonian tropical forest canopies", Remote Sensing of Environment 112 (2008) 2074–2087.

[21] M. N. Barros Filho a, F. J. A. Sobreira "Accuracy Of Lacunarity Algorithms In Texture Classification Of High Spatial Resolution Images From Urban Areas" The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B3b.,p.p 417-422, Beijing 2008.