Fibrous Dysplasia Characterization Using Lacunarity Analysis

Mirna S. Cordeiro¹ · André R. Backes² · Antônio F. Durighetto Júnior³ ·
Elmar H. G. Gonçalves⁴ · Jefferson X. de Oliveira¹

Published online: 26 August 2015
© Society for Imaging Informatics in Medicine 2015

Abstract Fibrous dysplasia (FD) is a developmental anomaly in which the normal medullary space of the affected bone is replaced by fibro-osseous tissue. This condition is typically encountered in adolescents and young adults. It affects the maxillofacial region and it can often cause severe deformity and asymmetry. Therefore, accurate diagnosis is critical to determine the appropriate treatment of each case. In this sense, computed tomography (CT) is a relevant resource among the imaging techniques for correct diagnosis of this condition. Thus, in this paper, we propose to analyze fibrous dysplasia through its texture pattern. To accomplish this task, we propose to use lacunarity analysis, a multiscale method for describing patterns of spatial dispersion. Results indicated lower lacunarity values for fibrous dysplasia in comparison to normal bone samples, an indication that their texture images are

more homogeneous, and a high separability between the classes when using principal component analysis (PCA) and decision trees for statistical analysis.

Keywords Lacunarity · Texture · Fibrous dysplasia · Computed tomography

Introduction

Fibrous dysplasia is a condition in which normal bone marrow is replaced by an abnormal proliferation of fibrous tissue, where there is newly formed immature bone [1]. It is a fairly common condition among bone tumors, but it is a rare disease in the general population. The exact incidence and prevalence are difficult to establish but account for about 5–7 % of benign bone tumors. As an expansile intraosseous lesion which affects the maxillofacial region, it can often cause severe deformity and asymmetry [2]. A genetic defect involving the Gs alpha protein appears to be the basis for this process [3, 4]. It typically presents with slow growth, progressive, painless, and unilateral [5]. However, in some cases, the damage may follow a more aggressive clinical course resulting in a rapid increase in pain symptoms [6]. Radiographically, fibrous dysplasia may present a large number of image patterns: appearing radiolucent, mixed, or radiopaque. The radiographic findings depend on the degree of mineralization and maturation of the lesion [7]. In this sense, the diagnosis of fibrous dysplasia can be difficult when using only conventional radiographic techniques [4]. Computed tomography (CT) appears as a relevant resource among the imaging techniques applied to the complex maxillofacial surgery [8].

Computer-based methods have been used for more accurate diagnosis, treatment planning, and monitoring of bone lesions [9, 10]. In addition, more recent approaches, such as

✉ André R. Backes
arbackes@yahoo.com.br

Mirna S. Cordeiro
mimacordeiro@usp.br

Antônio F. Durighetto Júnior
duriga@gmail.com

Elmar H. G. Gonçalves
medicos@clinicaclima.com.br

Jefferson X. de Oliveira
jexolive@usp.br

¹ School of Dentistry, University of São Paulo, Av. Professor Lineu Prestes, 2227-05508-000 São Paulo, SP, Brazil

² School of Computing, Federal University of Uberlândia, Av. João Naves de Ávila, 2121-38408-100 Uberlândia, MG, Brazil

³ School of Dentistry, Federal University of Uberlândia, Rua Acre 928, 38402-022 Uberlândia, MG, Brazil

⁴ School of Medicine, Federal University of Uberlândia, Av Marcos Freitas Costa, 180-38400328 Uberlândia, MG, Brazil

lacunarity analysis, have enabled us to quantify objectively the visual attributes obtained during the process of image analysis, showing promising results in the evaluation of major diseases.

Lacunarity is a measurement of the roughness of the texture pattern, commonly used in image analysis. It is obtained by measuring the spatial distribution of the gaps in the image. It enables us to quantify the texture appearance of an image so as to compare with other images [11]. This method characterizes the spatial distribution of an image, including an average proportion in the characterization of the size and shape of the subunits contained in the image [12]. It characterizes the way the pixels are distributed and arranged in a particular region of the image, i.e., it quantifies how the space is filled [13, 14]. Thus, lacunarity is a feasible feature to measure textures in terms of gap distribution [11, 12].

Therefore, this study aimed to analyze fibrous dysplasia by means of digital image analysis using helical computed tomography and lacunarity analysis to quantify the texture pattern from both normal and dysplastic bone areas.

Material and Methods

Image Acquisition

We performed this descriptive and exploratory study of fibrous dysplasia at Diagnostic Stomatological Clinic of the Faculty of Dentistry, University of Uberlândia - FOUFU. It was previously reviewed and approved by the Ethic Approval Board (CEP/UFU269/11). Initially, we retrieved material in the clinical digital database, which comprises all cases diagnosed from 1970 to the present date, the data of all patients previously diagnosed with fibrous dysplasia. A total of 10 patients were confirmed from clinical and radiographic criteria. We excluded some patients who had systemic conditions, which are known to alter the normal bone structure such as osteopenia, osteoporosis, osteogenesis imperfecta, and hyperparathyroidism. In addition, we also excluded those patients which were using drugs that could interfere with bone activity, undergoing radiotherapy, or were pregnant.

To describe a fibrous dysplasia sample, we collected demographic (age and sex) and clinical (location, size, duration of the lesion, type of treatment, and preservation) data of all cases, by analyzing the medical records of patients (who were identified by their number).

After the initial survey of the cases, we performed new CT scans for each patient selected. CT scans were performed in accordance with the regulations of radiation protection at the Department of Medical Radiology, Hospital de Clínicas at the Federal University of Uberlândia. We used a helical CT scanner (Somatom Spirit, Siemens®, Germany, two channels), and the images were subsequently evaluated by a viewing and

manipulation program of volumetric images located in this department, which were interpreted by experienced radiologists.

We evaluated these digital images in an independent workstation (DELL PRECISION 420 Windows XP) containing the program Vitrea® version 3.4.2 (Vital Images Inc., Plymouth, MN, USA) in DICOM (Digital Imaging and Communications in Medicine). These are axial and coronal images with cuts of 2 mm, reconstruction interval of 1 mm, matrix 512×512 size, pitch 1:1, and FOV of 17.4×17.4 cm for axial cuts and 18.2×18.2 cm for coronal cuts. We acquired both axial and coronal cuts, i.e., no image was reformatted. We carried out the description and the predominant tomographic pattern in each patient, which can be cystic, mixed, or sclerotic [15]. In our samples, six patients presented a predominant mixed pattern, while the remaining were classified as sclerotic. No patient presented a cystic pattern.

Subsequently, we selected distinct areas of lesion using the scale of Hounsfield to assess the degree of attenuation of the image [8, 12]. After the selection of the areas, there was the demarcation of three regions of interest (ROIs) in the dysplastic and contralateral normal bone (Fig. 1). These areas comprise a portion of the texture image of $W \times W$ pixels size, the first area presenting the highest density, the second area an intermediate density, and the third the lowest density.

Lacunarity

Texture is usually described as one of the most important visual attributes present in an image. It is a characteristic that enables us to distinguish different regions of the image, and as a consequence, it contributes to the process of recognition, analysis, description, and classification of digital images [16, 17].

One important approach to describe the texture appearance of an image is through lacunarity. It has been proposed by Mandelbrot, who noticed that different texture patterns presented the same fractal dimension; thus, a different measurement of the texture's roughness was necessary [18].

Fig. 1 Example of texture samples extracted from a tomographic scan. *Left:* normal bone samples; *right:* dysplastic bone sample; *middle:* positions where samples were extracted

Lacunarity is a measurement of the spatial distribution of gaps along the texture pattern, where we measure these gaps considering a specific size. This makes lacunarity a scale-dependent measurement of the texture's roughness [11, 18].

Literature presents many different approaches to compute lacunarity. Among these approaches, one of the most known is the gliding-box algorithm [11, 19]. Developed for binary images, this method computes lacunarity by gliding a box of size r over the image. From this idea, many authors have proposed different methods for dealing with grayscale images. In general, these methods are based on the differential box counting (DBC) method [13, 14, 20]. In this work, we consider the approach proposed by Du and Yeo to compute the lacunarity of a grayscale texture [14]. For each $r \times r$ gliding box, we computed the relative height of the current box

$$n_r(i, j) = \lceil \frac{v}{r} \rceil - \lceil \frac{u}{r} \rceil$$

where $\lceil x \rceil$ computes the smallest integral value that is not less than x , i and j are the image coordinates where the box is placed, and u and v are the minimum and maximum pixel values inside the box, respectively. Then, we compute the probability distribution $P(M, r)$, where M represents each possible value for the relative height $n_r(i, j)$

$$P(M, r) = \sum_{i,j} \delta(n_r(i, j), M)$$

where $\delta(x, y)$ is Kronecker's delta

$$\delta(x, y) = \begin{cases} 1, & x = y \\ 0, & x \neq y \end{cases}$$

Finally, we compute the probability density function $Q(M, r)$

$$Q(M, r) = \frac{P(M, r)}{\sum_M P(M, r)}$$

and the lacunarity for a box size r is defined as

$$A(r) = \frac{\sum M^2 \cdot Q(M, r)}{(\sum M \cdot Q(M, r))^2}$$

Image Pre-processing

We usually perform CT scans using a matrix of 512×512 size. This limited size affects the selection of some texture samples due to the small regions of some structures. This is the case of the normal bone region, which is relatively small in comparison to the affected bone area (Fig. 2). Thus, to properly evaluate the texture sample by using the lacunarity analysis, it is important to obtain a representative area of interest.

To improve this analysis, we proposed to resize the original CT scan images to three times their original size, i.e., an image

Fig. 2 Size comparison between the image regions studied. *Left*: dysplastic bone area; *right*: normal bone area

of 512×512 size was resized to 1536×1536 size. We opted by this increase in the image scale in opposition to other scale values as this choice demonstrated superior performance for the lacunarity analysis. To perform this resizing, we used bicubic interpolation [21]. We opted to use this method as it preserves the fine detail of the image while providing a resulting image which is smoother and has fewer interpolation artifacts in comparison to images obtained by other interpolation methods.

To evaluate the performance of different scale values, we considered the average and standard deviation of the lacunarity values computed for each set of cuts. Figure 3 shows the sum of the intersection between the average curves of the lacunarity values for dysplastic bone area and normal bone area in both axial and coronal cuts. We noticed that coronal images provide a better combination of average and standard deviation for the lacunarity, so that they present a small overlap of intervals between dysplastic and normal bone samples, especially when we resize the original CT scan images to three times their original size.

Another benefit from the resizing process is that the box size used in the lacunarity method is now able to evaluate the pixels of the image at smaller scales. When using the minimum box size, $r=2$, we are able to analyze a small region of 2×2 pixels of the image. By resizing the image to three times its original size, this region of 2×2 becomes 6×6 pixels size. Thus, using the minimum box size, $r=2$, we are able to analyze the small transitions between the pixels which could not be considered in the original size of the image.

In the sequence, we selected three regions of interest (ROIs) in the dysplastic and contralateral normal bone, as described in “Image Acquisition”, for coronal and axial images. We performed this task for each one of our 10 patients. These ROI areas correspond to a portion of the texture image of $W \times W$ pixels size, and in our tests, we used $W=33$. We selected this value of W as it is the maximum window size that fits in the normal bone region of the resized image. Here, we consider each selected ROI as a texture sample. Then, we computed the lacunarity for each texture sample.

Fig. 3 Sum of the intersection between the average curves of the lacunarity values for dysplastic bone area and normal bone area in both axial and coronal cuts

As described in “Lacunarity”, lacunarity is a scale-dependent measurement for describing texture patterns. Thus, we considered different r values to compute this measurement for each texture sample. As the texture sample selected is 33×33 pixels size, we chose to use small r values, in this case, $r = \{2, \dots, 10\}$. We opted for this set of r values as they enable us to glide the box during the lacunarity calculus longer than a larger box. In consequence, the method is able to analyze different portions of the image individually. Moreover, for each r value, we computed the average lacunarity value obtained for the three extracted samples.

Decision Tree

A decision tree is a simple, but powerful tool, for decision analysis. It is a classification method based on inductive learning. Its goal is to create a tree model where each branch represents a decision rule applied over an attribute of the sample, while the leaf node of the tree represents the most probable classification [22].

A well-known example of this classification method is the medical diagnosis, where the tree model maps the symptoms of a patient to the most probable diagnosis.

In this work, we used the C4.5 algorithm to build the decision tree. At each node, this algorithm selects the attribute that most effectively splits the set of samples into two subsets representing different classes of data. Both attribute and splitting criterion are selected based on the normalized information gain, which uses the concept of information entropy [22].

Principal Component Analysis

Principal component analysis is an important tool for identifying patterns in data, thus evidencing its similarities and

differences. It is an orthogonal linear transformation that transforms the original data to a new coordinate system, where each coordinate is called a component. In this new system, the first component has the largest possible variance, the second component has the second largest variance, and so on [23].

It is especially important for the analysis of data represented by variables possibly correlated. In this case, principal component analysis (PCA) maps these variables into a set of values of linearly uncorrelated variables, thus improving its posterior analysis.

Grubbs' Test

Grubbs' test is a statistical test that detects outliers assuming a normally distributed population. It is based on the difference of the mean and the most extreme samples considering the standard deviation of the population of samples. The result of this test is the probability that the sample belongs to the set [24]. This test evaluates a univariate data, so that we applied it for the average lacunarity value computed using a single r value. We considered the significance level $\alpha = 0.05$.

Results

By analyzing the average lacunarity computed from normal and dysplastic bone samples in tomographic scans, we found evidence that fibrous dysplasia in coronal cuts presents a lower lacunarity value, an indication that their texture images present a more homogeneous gap distribution than those from normal bone area [11, 12].

Using a decision tree, we are able to correctly classify 84.21 % of the bone samples [22]. This is achieved using only

two lacunarity values, $\Lambda(2)$ and $\Lambda(3)$. After applying PCA over these lacunarity values, we increase this success rate to 89.47 % [23].

Discussion

Firstly, we computed the average lacunarity value for the three extracted bone samples. We performed this step for both dysplastic and normal bone regions selected from coronal and axial images from each patient. By using the average, we avoid abrupt oscillations in the lacunarity due to grayscale variations in a bone region, as it may present darker and brighter areas in the same region. As a result, each patient is represented by four datasets of average lacunarity values: (i) coronal normal bone, (ii) coronal dysplastic bone, (iii) axial normal bone, and (iv) axial dysplastic bone.

Once we have the average lacunarity values, we investigated the presence of outliers in the samples. We applied Grubbs' test on the average lacunarity value computed using $r=2$. As a result, three samples were discarded: two from axial normal bone and one from coronal normal bone. No samples from dysplastic bone datasets were discarded.

After removing the outliers, we performed some statistical analyses in the lacunarity data. To accomplish that, we considered axial and coronal cuts as independent sets of images. We separated the samples in order to evaluate whether there might be a difference in the discrimination ability of the cuts. For this test, we focused on the simple analysis of the average and standard deviation of the lacunarity values computed for each set of cuts, as shown in Fig. 4. It is possible to note that fibrous dysplasia in tomographic scans presents a lower lacunarity in comparison to normal bone samples. According to literature, this is an indication that their texture images present a more homogeneous gap distribution than those from normal bone area [11, 12]. We also noticed that the distance between average lacunarity curves from normal and dysplastic bone is larger for coronal cuts (Fig. 4b) than for axial cuts (Fig. 4a). To assure a better separation of the samples, it is also important that the samples present a small standard deviation. This guarantees that different types of samples (normal and dysplastic) present a small intersection in their values, i.e., the similarities between different types of data are small. In this sense, coronal cuts provide better information of the lesion in comparison to axial cuts. Coronal cuts provide a better combination of average and standard deviation, so that there is little overlap of values.

The reason why coronal cuts provide better information is not clear, since there are no significant differences in the acquisition process and in the visual aspect of the texture. One possible explanation for this is that an axial cut provides a transverse view and it could mask some aspects of the texture

Fig. 4 Average lacunarity values computed for both normal and dysplastic bone using different r values. **a** Axial cuts; **b** coronal cuts

of the lesion, while a coronal cut gives a frontal view and it is clearer for analysis purposes.

In the sequence, we evaluate the worth of each lacunarity value for classification purposes. We accomplished this task by considering the predictive ability of each lacunarity value along with the degree of redundancy between them [25]. Results indicated that the lacunarity computed for $r=2$ and $r=3$ is highly correlated with the class (normal and dysplastic bone). Figure 5a shows the plot of these lacunarity values. The plot of these values shows that there exists a considerable separation between the two types of samples. Thus, we computed a decision tree in order to create a classification strategy for the samples, as shown in Fig. 5b. A total of 84.21 % of the samples are correctly classified in their respective classes. This is an excellent result if we consider the small texture sample used (33×33 pixels size) due to the difficulty of extracting relevant image samples of the normal bone area of the tomographic scans. However, only one lacunarity value was used. The decision tree was not able to exploit the second attribute

Fig. 5 Distribution and classification of the samples according to their lacunarity values, $\Lambda(r)$, computed for $r=2$ and $r=3$. **a** Plot of the two lacunarity values; **b** computed decision tree. Lacunarity computed using $r=2$; $\Lambda(2)$ is enough to classify the samples between normal and dysplastic bone with an accuracy of 84.21 %

as both attributes are oriented over the same line. Thus, we decided to apply a principal component analysis (PCA) over these values [23]. As we are using only two values of lacunarity (computed using $r=2$ and $r=3$, respectively, $\Lambda(2)$ and $\Lambda(3)$), we are able to compute two components ($C1$ and $C2$) as follows:

$$C1 = 0.7079 * \Lambda(2) + 0.7063 * \Lambda(3)$$

$$C2 = -0.7063 * \Lambda(2) + 0.7079 * \Lambda(3)$$

Figure 6a shows the plot of the first ($C1$) and second ($C2$) components. The plot of the first and second components shows that PCA helps to improve the separation of the two classes of samples. Thereby, we also decided to compute a new decision tree for the two components, as shown in Fig. 6b. Due to the PCA, this new decision tree is able to exploit both attributes to classify the samples and it achieves an accuracy of 89.47 %. As we can see, by using a simple linear transformation such as PCA, we are able to perform a more accurate classification between normal and dysplastic bone than single lacunarity values.

Statistical results of the lacunarity show that this is a feasible approach to separate the normal from dysplastic bone samples. In routine clinical practice, this approach could be used to increase the accuracy of a diagnosis, thus preventing

Fig. 6 Distribution and classification of the samples according to the two principal components computed using PCA. **a** Plot of the two principal components ($C1$ and $C2$); **b** computed decision tree. By using the two components, it is possible to classify the samples between normal and dysplastic bone with an accuracy of 89.47 %

the need for more invasive steps, such as biopsy or surgery. However, its use is not limited to these tasks. Lacunarity could also be used to quantify the severity of disease or to differentiate benign from malignant tumors. Literature presents various examples of the use of lacunarity in other scenarios, such as to assess osteoporosis [12], microvascular morphology [26], to analyze the behavior of prostate cancer [27] and breast tumor lesions [28], and to measure cell cancer behavior [29].

Conclusions

This paper has presented a novel approach of fibrous dysplasia characterization through lacunarity. Fibrous dysplasia characterization is a difficult task due to the similarity that exists between it and the normal bone samples and the limited region of the normal bone of the tomographic scans used in the comparison.

Samples of normal bone and fibrous dysplasia were collected and lacunarity analysis was performed. Results

indicated that fibrous dysplasia in tomographic scans presents lower lacunarity in comparison to normal bone samples, an indication that their texture images are more homogeneous. Moreover, statistical analysis using principal component analysis (PCA) and decision trees has shown a high separability between the classes.

Acknowledgments The authors are very thankful to the radiology technicians Ronei Alves Ferreira and Divino Sebastião da Silva for the support during achievement of the computed tomographic scans of this study. The authors thank FAPEMIG, CNPq, and PROPP-UFU for financial support. André R. Backes gratefully acknowledges the financial support of CNPq (National Council for Scientific and Technological Development, Brazil) (Grant #301558/2012-4).

References

- Reichart PA, Philipsen HP: Odontogenic tumors and allied lesions. Quintessence, London, 2004
- Campanacci M: Bone and soft tissue tumors: clinical features, imaging, pathology and treatment, 2nd edition. Springer, New York, 1999
- Brannon RB, Fowler CB: Benign fibro-osseous lesions: a review of current concepts. *Advances in Anatomic Pathology* 8(3):126–143, 2001
- MacDonald-Jankowski D: Fibrous dysplasia: a systematic review. *Dentomaxillofacial Radiology* 34(4):196–215, 2009
- Ricalde P, Horswell BB: Craniofacial fibrous dysplasia of the frontoorbital region: a case series and literature review. *Journal of Oral and Maxillofacial Surgery*. 59:157–168, 2001
- Resnick D, Niwayama G: Diagnosis of bone and joint disorders, 2nd edition. Saunders, Philadelphia, 1988
- Goaz PW, White SC, Pharoah MJ: Oral radiology: principles and interpretation. 4th ed. Mosby, St. Louis, 1994
- Seeram E: Computed tomography: physical principles, clinical applications and quality control, 2nd edition. Saunders, Philadelphia, 2001
- Heo MS, Park KS, Lee SS, Choi SC, Koak JY, Heo SJ, Han CH, Kim JD: Fractal analysis of mandibular bony healing after orthognathic surgery. *Oral Surg Oral Med Oral Pathol Oral Radiol Endod* 94(6):763–7, 2002
- Rabelo GD, Beletti ME, Dechichi P: Histological analysis of the alterations on cortical bone channels network after radiotherapy: A rabbit study. *Microsc Res Tech* 73(11):1015–8, 2010
- Allain C, Cloitre M: Characterizing the lacunarity of random and deterministic fractal sets. *Phys Rev A* 44(6):3552–3558, 1991
- Dougherty G, Henebry GM: Lacunarity analysis of spatial pattern in CT images of vertebral trabecular bone for assessing osteoporosis. *Medical Engineering & Physics* 24(2):129–138, 2002
- Dong P: Test of a new lacunarity estimation method for image texture analysis. *International Journal of Remote Sensing* 21(17):3369–3373, 2000
- Du G, Yeo TS: A novel lacunarity estimation method applied to SAR image segmentation. *IEEE Trans Geoscience and Remote Sensing* 40(12):2687–2691, 2002
- Lupescu I, Hermier M, Georgescu SA, Froment JC: Helical CT and diagnostic evaluation of cranio-facial fibrous dysplasia. *J Radiol* 82(2):145–9, 2001
- Myint SW, Lam N: A study of lacunarity-based texture analysis approaches to improve urban image classification. *Computers, Environment and Urban Systems*. 29(5):501–523, 2005
- Borys P, Krasowska M, Grzywna ZJ, Djamgoz MBA, Mycielska ME: Lacunarity as a novel measure of cancer cells behavior. *Biosystems* 94(3):276–281, 2008
- Mandelbrot B: The fractal geometry of nature. Freeman, San Francisco, 1982
- Facon J, Menoti D, de Albuquerque Araújo A: Lacunarity as a Texture Measure for Address Block Segmentation. In: Progress in Pattern Recognition, Image Analysis and Applications, 10th Iberoamerican Congress on Pattern Recognition, CIARP 2005, Havana, Cuba, November 15–18, 2005. Proceedings. vol. 3773 of Lecture Notes in Computer Science, Springer, 2005, pp 112–119
- Sarkar N, Chaudhuri BB: An Efficient Approach to Estimate Fractal Dimension of Textural Images. *Pattern Recognition* 25(9):1035–1041, 1992
- Yuan S, Abe M, Taguchi A, Kawamata M: High Accuracy Bicubic Interpolation Using Image Local Features. *IEICE Transactions* 90-A(8):1611–1615, 2007
- Quinlan R: C4.5: Programs for Machine Learning. Morgan Kaufmann, San Mateo, California, 1993
- Jolliffe IT: Principal Component Analysis. Springer Verlag, Series in Statistics, 2002
- Grubbs FE: Procedures for detecting outlying observations in samples. *Technometrics* 11(1):1–21, 1969
- Hall MA: Correlation-based Feature Subset Selection for Machine Learning. University of Waikato, Hamilton, New Zealand, 1998
- Gould DJ, Vadakkan TJ, Poché RA, Dickinson ME: Multifractal and lacunarity analysis of microvascular morphology and remodeling. *Microcirculation* 18(2):136–51, 2011
- Nevesa LA, Nascimento MZ, Oliveirac DLL, Martinsd AS, Godoye MF, Arrudaf PFF, de Santi ND, Machadoa JM: Multi-scale lacunarity as an alternative to quantify and diagnose the behavior of prostate cancer. *Expert Systems with Applications* 41(11):5017–5029, 2014
- Soares F, Janela F, Pereira M, Seabra J, Freire MM: 3D lacunarity in multifractal analysis of breast tumor lesions in dynamic contrast-enhanced magnetic resonance imaging. *IEEE Trans Image Process* 22(11):4422–35, 2013
- Borys P, Krasowska M, Grzywna ZJ, Djamgoz MB, Mycielska ME: Lacunarity as a novel measure of cancer cells behavior. *Biosystems* 94(3):276–81, 2008