Quantification of Trabecular Bone Porosity on X-Ray Images

Khaled Harrar
Faculty of Engineering, University of M'Hamed Bougara, Avenue de l'independence, 35000 Boumerdes, Algeria
Email: harrar_k@umbb.dz

Rachid Jennane
I3MTO Laboratory, University of Orleans, EA 4708, 8 rue Léonard de Vinci BP 6744, 45067 Orléans Cedex 2, France
Email: Rachid.Jennane@univ-orleans.fr

***Abstract*—Osteoporosis is a disease characterized by low bone mass and deterioration of the micro-architecture of the bone tissue, which lead to increased bone fragility and therefore, an increased risk of fracture. The purpose of this work is to quantify the porosity of radiographic bone images in order to characterize osteoporosis. Two methods are used to characterize radiographic bone images, lacunarity and star volume distribution. The first method is based on fractal analysis and the second on the evaluation of the bone medullar space. 2D bone radiographic images from two populations composed of 80 control subjects and 80 patients with osteoporotic fractures are analyzed. The results show a good discrimination between the two groups.**

***Index Terms*—bone mineral density, lacunarity, star volume osteoporosis, radiography**

I. Introduction

If bone loss is unavoidable and normal with aging, when can we then talk about osteoporosis? The disease is defined as a bone fragility which results from a gradual decrease of bone density combined with a deterioration of the "architecture" of the bone. This disease affects a large part of the population from a certain age and promotes fractures. Therefore, prevention is the subject of numerous studies. If treatments exist, we do not know yet the diagnosis inexpensively. The bone becomes porous (hence the name osteoporosis) and more likely to break. Here we must emphasize the importance of these two processes - decreased bone density and deterioration of bone microarchitecture - in an adequate definition of osteoporosis. The assessment of these two processes would be a reliable diagnosis. However, the test used in the clinical routine is only based on the measurement of the bone density and doesn't quantify the microarchitecture of the bone. In addition, bone density exam results, are interpreted in terms of an increased risk of fractures, the risk being confused with the disease itself. How to judge the porosity of bone using a radiographic image? For several years, many researchers considered models to describe irregular processes that seem relevant. This irregularity is directly related to fractal objects. A fractal is defined as a mathematical set or physical system of irregular or fragmented shape that is created following deterministic or stochastic rules [1]. The measured parameter is the fractal dimension D.

In recent years, fractal analysis of plain radiographs has been employed to assess the trabecular bone structure, but almost all these studies have been focused on the fractal dimension evaluated by different approaches (variance method, surface area, Fourier transformation, ...) [2] and [3], and just few works have been dedicated to lacunarity analysis [4] and [5]. The fractal dimension which is a function of the roughness of the texture, alone is not sufficient to differentiate bone textures. To get an efficient characterization, and quantify the degree of porosity of trabecular bone, the lacunarity can be a valuable adjunct. This later which is a second-order fractal metric is able to better characterize and provide information about the amount of "porosity" of structures in bone images [6].

Other methods exist for assessing bone architecture, in particular, stereological estimators. The star volume distribution (SVD) has been recognized as a good estimator to assess bone architecture [7]. The SVD is defined as the mean volume of all the parts of an object which can be seen unobscured in all directions from a particular point with the mean value taken over all points inside the object. It is defined for any type of objects including cavities like marrow space and networks like the trabecular system.

A lot of work has been done to characterize the trabecular bone architecture. Buckland-Wrigh *et al*. [8] used high-definition macroradiography and fractal signature analysis to quantify the trabecular organization in lumber vertebrae and knee. They characterized architectural differences between groups of patients with low and high BMD. As part of a larger study, the Osteodent project, Geraets *et al*. [9] investigated if the trabecular pattern on dental radiographs can be used to predict BMD and to identify the subjects with osteoporosis and increased risk of osteoporotic fractures. Jennane *et al*. [10] presented a series of 3D skeleton-based image processing techniques for evaluating the

Manuscript received March 5, 2015; revised April 21, 2015.

doi: 10.12720/jiii.3.4.280-285

micro-architecture of large scale disordered porous media. The proposed hybrid skeleton method combine curve and surface thinning methods with the help of an enhanced shape classification algorithm. Results on bone demonstrate the ability of the hybrid skeleton method to provide significant topological and morphological information. Harrar *et al*. [11] have developed and validated a new method to assess bone microarchitecture on radiographs. Taking into account the piecewise fractal nature of the data, a piecewise fractional Brownian motion was used to characterize the trabecular bone network. Based on the Whittle estimator, a new method for calculating the Hurst exponent H is developed to better consider the piecewise fractal nature of bone radiograph images. Their findings demonstrate that the new estimator proposed provides effective results in terms of discrimination of the subjects suffering from osteoporosis and is better adapted to bone radiograph image analysis.

In this study, to quantify porosity, X-ray radiographic images taken at the calcaneus site are used. Lacunarity is used as a statistical method for texture analysis and the SVD as a structural method is used for the characterization of the bone architecture. The interest of this work is to compare the ability of the two methods to discriminate between two populations composed of 80 healthy cases (CC) and 80 osteoporotic patients (OP).

II. Materiel and Methods

A. Subjects

All the OP patients (fracture cases) and CC subjects voluntarily entered the study after written informed consent. Patients were systematically screened from all women attending the bone densitometry unit for routine clinical care. This study involved 160 women, 80 controls aged 68.93 ± 9.78 SD and 80 osteoporotic fracture cases aged 71.34 ± 10.55 SD. No significant difference was found for the age (p-value NS). All the patients filled out an osteoporosis risk questionnaire that included: age, personal and family history of fracture, menopausal status (time since menopause), use of hormone replacement therapy (HRT), other medication and other diseases (rheumatoid arthritis, etc.).

B. Image Acquisition

Images were obtained on calcaneus bone with a direct digital X-ray prototype (BMA™, D3A Medical Systems, Orleans, France) [12]. We used the calcaneus because of the limited soft tissues surrounding this bone. Soft tissues could increase the variability of the method. The study of the calcaneus seems relevant because it contains 90% of trabecular bone [2] and is a good predictive site of fracture in terms of bone mineral density [2]. The devices for the study were cross-calibrated. The cross-calibration procedure has been described in [13]. The same radiographic parameters were used for the prototypes. Focal distance was set at 1.15 m. The X-ray parameters were 55 kV and 20 mAs for all patients. Scanning the heel permitted the selection of a similar measurement site (ROI) for each subject by using anatomical landmarks as previously described in [12]. These anatomical landmarks were localized by the operator on the image, allowing positioning of the ROI (1.6 × 1.6 cm2) performed by the software device (Fig. 1).

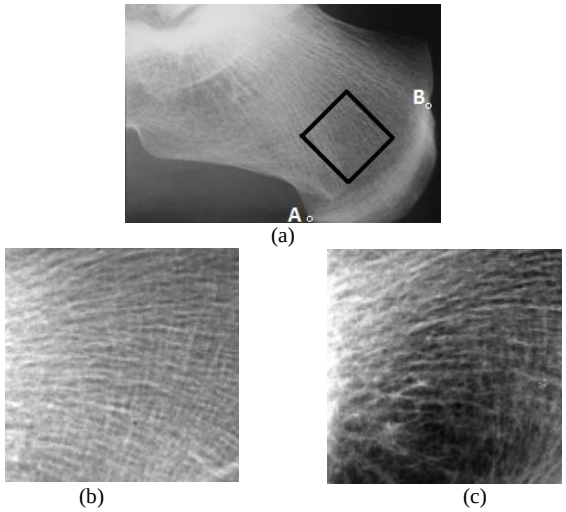


Figure 1. ROI for texture analysis at the calcaneus with the two anatomical landmarks A and B (a), a CC image (b) and an OP image (c).

During the acquisition, storage or scanning process of the images, a noise is generated, this affect the quality of the radiographic image. To improve the quality of the image, usually a filter is necessary. This will improve the high frequencies of the image that contain noises, without changing the low frequencies that are representative of the information content of the image, i.e. the trabeculae. An interesting filter in medical imaging is the nonlinear median filter, it works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. The pattern of neighbours is called the "window", which slides, pixel by pixel over the entire image. The median value is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value. In our case, we used a filter size of 3x3.

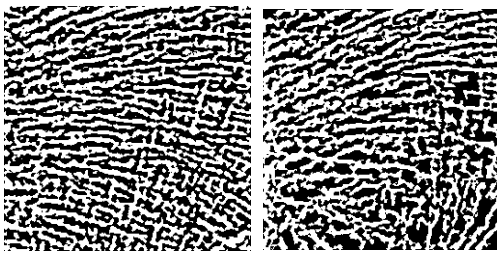


Figure 2. Binary images related to the previous ROIs. (a) CC binarized image, (b) OP binarized image.

ROI images were first binarized using the algorithm described by White and Rudolph [14], which was used for measuring the morphologic features of the trabecular bone architecture. Each ROI image was first smoothed using a low-pass Gaussian filter (sigma = 21 pixels, kernel size = 10) to remove large-scale variations in the

image. The smoothed image was then subtracted from the original, and a 128-gray-level value was added to each pixel of the subtracted image. The resulting image was then binarized using a global threshold value of 128 (Fig. 2) [14], which segmented the image into the bone (gray level of 255) and marrow (gray level of 0). Finally, an additional pruning step was applied to the resulting image to remove the residual small size artefacts (< 5 pixels).

C. Lacunarity: Gliding-Box Algorithm

In geometry, lacunarity (Λ) is a measure of how a fractal fills space. Lacuna means gap (more gaps = higher lacunarity). Authors have proposed various methods in the literature for calculating lacunarity [15]-[17]. In this study we have used the gliding-box method. The gliding-box algorithm consists to sample an image using overlapping square windows of length ε. It is based on a localized mass calculation [1] and [16]; a unit box of size r is chosen and the number of set points, m, within the box (the mass) is counted. This procedure is then repeated, creating a distribution of box masses $B(m, \varepsilon)$, where B is the number of boxes with m points and length side ε. This distribution is then converted into a probability distribution, $P(m, \varepsilon)$, by dividing $B(m, \varepsilon)$ by the total number of boxes $N(\varepsilon)$ of size ε. The lacunarity at scale ε is defined by the mean-square deviation of the fluctuation of mass distribution probability $P(m, \varepsilon)$ divided by its square mean. The Gliding-box lacunarity, Λ_{GB} is then defined as:

$$\Lambda_{GB}(\varepsilon) = \frac{K^{(2)}(\varepsilon)}{K^{(1)}(\varepsilon)^2} = \frac{\sum_m m^2 P(m,\varepsilon)}{[\sum_m m\, P(m,\varepsilon)]^2} \quad (1)$$

An extended version of lacunarity and the gliding-box concept was introduced by Plotnick *et al*. [18] based on a random binary map (0 for empty and 1 for occupied):

$$\Lambda(\varepsilon) = 1 + \frac{\sigma^2(\varepsilon)}{\mu^2(\varepsilon)} \quad (2)$$

where μ is the mean and σ^2 is the variance of the number of occupied sites at scale r. Lacunarity can be compared independently of image density by normalizing (2) [15]:

$$\Lambda_{norm} = 2 - \left(\frac{1}{\Lambda} + \frac{1}{\Lambda^c}\right) \quad (3)$$

where Λ^c is complementary lacunarity (obtained by calculating the lacunarity of the complement binary image). Λ_{norm} is denoted below as Λ for convenience..

D. Star Volume Distribution

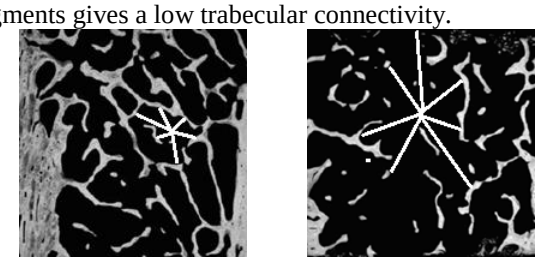
This method has been widely exploited for the measurement of porous materials, particularly cement and rock [7]. It is based on the study of medullary spaces: from any point in the marrow space, radii are projected in all directions of space. These radii stop when they meet trabeculae. The holl of these radii constitute a kind of "star". The average size of the radii of the star gives an idea of the perforation of the bone trabecular tissue. The more the lengths of the radii are greater, the larger the network is disconnected (Fig. 3).

The star volume $(V^*_{m.space})$ is defined by:

$$V^*_{m.space} = \frac{\pi}{3}\overline{l_0^3} \quad (4)$$

where l_0 is the mean length of the segments in all directions.

By analyzing the distribution of the medullary space, an indirect assessment of the organization of the trabecular network is obtained. Significant size of the segments gives a low trabecular connectivity.



(a) (b)

Figure 3. Illustration of the concept of the SVD. (a) for a CC image, (b) for an OP image.

Fig 3.b show large size of the star in osteoporotic patient compared to the healthy one (Fig 3.a), this reflects the loss in trabecular bone connectivity.

To estimate the SVD, thresholding and surrounding the region of interest are needed in order to avoid detection of overflows of the boundaries of the image.

For each pixel of the medullary space of the image, a scanning is performed in all directions, when a trabecula is found; the size of the segment corresponding to the angle (direction) is calculated. The operation is repeated for all angles (from 0 ° to 360 °), the average size of the segments is calculated. Finally, the star volume corresponds to the mean of segment sizes for each pixel.

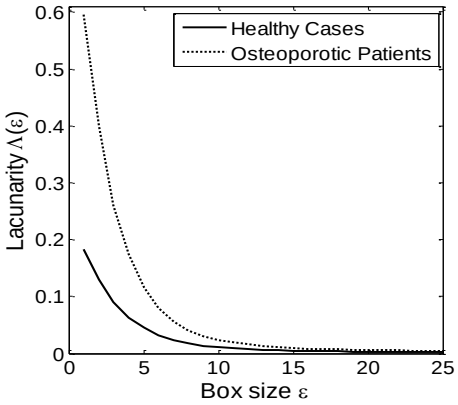


Figure 4. Lacunarity curves of images of figure 1.

III. Results and Discussion

A. Lacunarity Analysis

An example of lacunarity applied on the ROIs of Fig. 1 is shown for different box sizes ranging from 1 to 25 pixels (Fig. 4). The OP image provides higher Lacunarity, due to significant presence of holes in the image, related to the loss of bone mass (Fig. 1b). Lower lacunarity is

observed for the CC image (Fig. 1a) due to a lower bone loss. As the size of boxes increases, the lacunarity deceases. For small sizes of boxes, lacunarity is high due to large holes. For larger sizes, the lacunarity is lower due to the reduced number of holes. The appearance of the texture is strongly affected by the lacunarity due to the spatial heterogeneity of structures. The more lacunar image (Fig. 1b) indicates that there is less structures in the image. The lacunarity is a powerful texture analysis feature for quantifying the porosity of complex shapes such as bone microarchitecture.

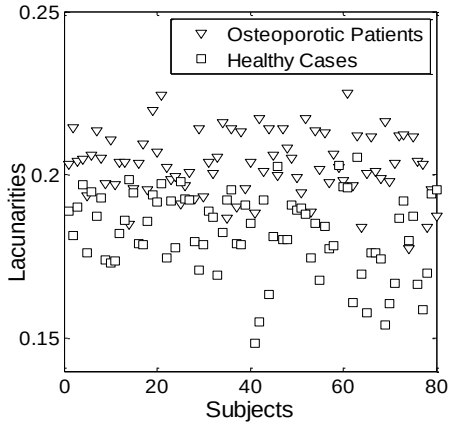
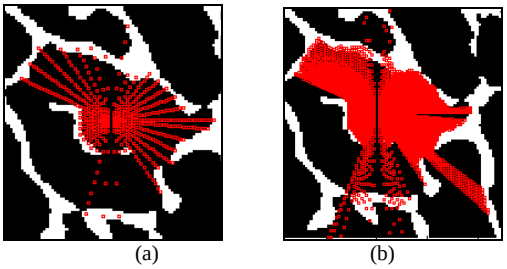


Figure 5. Estimated lacunarity values for the two populations.

Lacunarities estimated for the two populations are illustrated in Fig. 5, we can notice a good discrimination of the two groups, the average lacunarity of the osteoporotic patients is higher compared to that of the control subjects. Due to loss of bone mass and trabecular network connectivity, the trabeculae becomes very thin. However, some overlapping between the two populations is noticed.

B. SVD Analysis

The computational efficiency is mandatory for the SVD analysis. For timeliness, it is not necessary to scan all directions, a scan every 10 °is enough (Fig. 6.a).

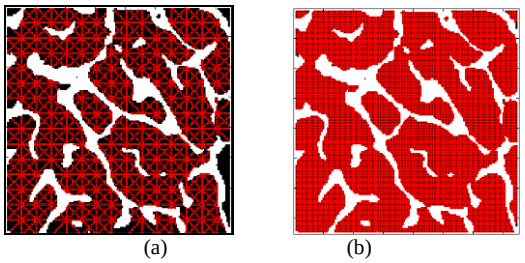


(a) (b)

Figure 6. Illustraion of the SVD method for a trabecular bone image with different angles. (a) α = 10 °, (b) α = 1°.

Fig. 6 a and b show a case of scanning a medullary space with different angles. As the angle decreases, porous space is fully scanned, but this is time consuming (14.11s for a step angle of 1 °compared to 1.31s for a step angle of 10 °). It should be noted also that the high rate of false alarms presented in Fig. 6.b is due to the discretization artifacts of the image. The results of the SVD method applied to the radiographic bone images of Fig. 1.a and b respectively are ($V^*_{m.space}$ = 14.09, time = 203.03s) and ($V^*_{m.space}$ = 20.28, time = 300.15s).

All our tests provided a high value of SVD feature OP images. This is mainly due to high discontinuity (porosity) of the trabecular network, resulting in an important marrow space. As a conclusion, the SVD method is well suited for the characterization of the porosity of trabecular boneon radiographic images. To overcome the problem of false alarms due to discretization artifacts of the image and the problem of the computation time for the SVM method, an improved algorithm was implemented. For a given pixel, the scanning is done only in eight preferred directions. The scanning pixels belonging to the marrow space is performed on these directions, avoiding aberrations results using tangents. Fig. 7 shows the approach used for the scanning of the medullary space. In Fig. 7.a, jumping is set to 2 pixels for the scan. In Fig. 7.b, the jump is set to 1 pixel, the image is fully scanned. In the first case, the advantage goes to the computation time, unlike in the latter where we noticed a long process time, the result of the scan is almost identical in both cases (Fig. 7.a and 7.b). Also we noticed that the trabeculae (white areas) were preserved.



(a) (b)

Figure 7. Improved scan of the medullary space to compute the SVD method, (a) by 10 pixels block, (b) for all pixels.

TABLE I. MEAN ±SD FOR LACUNARITY, SVD AND BMD, ESTIMATED FOR OP AND CT IMAGES AS WELL AS P-TEST VALUES

	CT	OP	*p*-value
Λ	0.182 ±0.012	0.193 ±0.010	1.82e-07
$V^*_{m.space}$	2.028 ±0.105	2.103 ±0.101	1.83e-05
BMD	0.836 ±0.119	0.732 ±0.137	5.30e-07

The performance of an estimator to discriminate the two populations was evaluated with the *p*-value statistical test using the rank sum Wilcoxon test [19]. We considered a highly statistical significant *p*-value (*p*-value < 0.001). Table I presents the results expressed as mean ± standard deviation (SD) for all the subjects. As can be seen in Table I, all the features separate significantly the OP patients and the CT subjects. The obtained *p*-values, 1.82e-07, 1.83e-05, and 5.30e-07 respectively for Λ, $V^*_{m.space}$ and BMD are significant. The best performance of discrimination is up to the lacunarity which performs well the porosity quantification of the trabecular network.

Fig. 8 illustrates the SVD estimated over the images of the two populations. As can be observed, the two populations can be discriminated. The SVD method

reveals high values for OP due to higher porosity related to the disorder of the trabecular network.

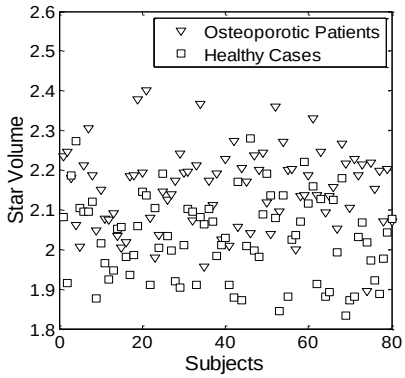


Figure 8. Estimated SVD values for the two populations.

In this work, we demonstrated the performance of two methods to discriminate between two groups (OP and CT). We highlighted the relationship between lacunarity and porosity of the trabecular network due to osteoporosis. Healthy subjects show low lacunarity values, whereas osteoporotic patients with risk of fracture have high lacunarity values (Fig. 5). Relationships between the SVD and osteoporosis were demonstrated. CT subjects have low porosity due to better connectivity of the trabecular bone network.

In terms of discrimination of the subjects, there is a variability in Table I, but the best performance is obtained by the lacunarity, which had the best ability to discriminate the subjects (p = 1.82e-07), a cut above the BMD (p = 5.30e-07). Moreover, the lacunarity is more accurate and reliable than the SVD, which provide a lower statistical significant test value (p = 1.83e-05), with more overlap between the two groups.

According to these results, we can conclude that SVD and lacunarity methods are reliable tools to detect bone diseases such as osteoporosis.

IV. Conclusion

The objective of this work was to implement two methods for the quantification of porosity on radiographic bone images. To achieve this task, two methods were compared. Lacunarity which showed good performances to discriminate between two populations of healthy and osteoporotic subjects. Lacunarity was lower for control cases, which indicates the characteristics of the distribution of the holes and the heterogeneity of the images. Our study suggests that the lacunarity which is a second order statistical statistic measure of the second order, can be helpful for characterizing the trabecular bone shape with sufficient sensitivity to distinguish different degrees of bone quality. Lacunarity analysis of trabecular texture is a promising additional diagnostic tool to complement the BMD in the assessment of bone quality for the characterization of osteoporosis and increased fracture risk prediction.

The star volume distribution method seems to be a useful tool for characterizing the trabecular bone tissutissue.

Further studies are needed to provide more information about the precise relationship between bone loss and porosity analysis parameters, to understand the exact mechanisms leading to bone fragility and to find new therapeutic strategies more effective in dealing with the consequences of osteoporosis and other metabolic bone diseases.

References

[1] B. B. Mandelbrot, *The Fractal Geometry of Nature*, Freeman & Co Ltd, new York, 1983, ch. 2, pp. 58-74.
[2] C. L. Benhamou *et al*., "Fractal organization of trabecular bone images on calcaneus radiographs," *J. Bone Miner. Res.*, vol. 9, no. 12, pp. 1909-1918, 1994.
[3] R. Jennane, W. J. Ohley, S. Majumdar, and G. Lemineur, "Fractal analysis of bone X-ray tomographic microscopy projections," *IEEE Trans. Med. Imaging*, vol. 20, no. 5, pp. 443-449, 2001.
[4] A. V. Nektarios, F. Mendoza, D. W. Sun, and P. Allen, "Texture appearance characterization of pre-sliced pork ham images using fractal metrics: Fourier analysis dimension and lacunarity," *Food Res. Int.*, vol. 42, no. 3, pp. 353-362, 2009.
[5] G. Dougherty and G. M. Henebry, "Lacunarity analysis of spatial pattern in CT images of vertebral trabecular bone for assessing osteoporosis," *Med. Eng. Phys.*, vol. 24, pp. 129-138, Mar. 2002.
[6] K. Harrar and L. Hamami, "An interconnectivity index for osteoporosis assessment in X-Rays images," *J. Med. Biol. Eng.*, vol. 33, no. 6, pp. 569-575, 2013.
[7] A. Vesterby, "Star volume in bone research a histomorphometrric analysis of trabecular bone structure using vertebral sections," *Ana. Rec.*, vol. 235, no. 2, pp. 325-334, 1993.
[8] J. C. Buckland-Wright, J. A. Lynch, and D. G. Macfarlane, "Fractal signature analysis measures cancellous bone organization in macroradiographs of patients with knee osteoarthritis," *Ann. Rheum. Dis.*, vol. 55, no. 10, pp. 749-755, 1996.
[9] W. G. M. Geraets *et al*., "Prediction of bone mineral density with dental radiographs," *Bone*, vol. 40, no. 5, pp. 1217-1221, 2007.
[10] R. Jennane, A. Almhdie, G. Aufort, and E. Lespessailles, "3D shape-dependent skeletonization method for trabecular bone characterization," *Med. Phys.*, vol. 39, no. 1, pp. 168-178, 2012.
[11] K. Harrar, L. Hamami, E. Lespessailles, and R. Jennane, "Piecewise whittle estimator for bone radiograph characterization," *Biomed. Signal Process. Control*, Elsevier, vol. 8, no. 6, pp. 657-666, 2013.
[12] E. Lespessailles *et al*., "Clinical interest of bone texture analysis in osteoporosis: A case control multicenter study," *Osteoporos. Int.*, vol. 19, no. 7, pp. 1019-1028, 2008.
[13] E. Lespessailles, C. Gadois, G. Lemineur, J. P. Do-Huu, and L. Benhamou, "Bone texture analysis on direct digital radiographic images: precision study and relationship with Bone Mineral Density at the os calcis," *Calcified Tissue Int.*, vol. 80, no. 2, pp. 97-102, 2007.
[14] S. C. White and D. J. Rudolph, "Alterations of the trabecular pattern of the jaws in patients with osteoporosis," *Oral Surg. Oral Med. O.*, vol. 88, no. 5, pp. 628-635, 1999.
[15] G. Dougherty, "A comparison of the texture of computed tomography and projection radiography images of vertebral trabecular bone using fractal signature and lacunarity," *Med. Eng. Phys.*, vol. 23, no. 5, pp. 313-321, 2001.
[16] C. Allain and M. Cloitre, "Characterizing the lacunarity of random and deterministic fractal sets," *Phys. Rev. Appl.*, vol. 44, no. 6, pp. 3552-3558, 1991.
[17] R. Voss, "Random fractals: Characterization and measurement," in *Scaling Phenomena in Disordered Systems*, R. Pynn and A. Skjeltorp, Ed., New York: Plenum, 1985, pp. 1-11.
[18] R. E. Plotnick, R. H. Gradner, W. W. Hargrove, K. Prestegaard, and M. Perlmutter, "Lacunarity analysis: A general technique for the analysis of spatial patterns," *Phys. Rev. E.*, vol. 53, no. 5, pp. 5461-5468, 1996.
[19] F. Wilcoxon, "Individual comparisons by ranking methods," *Biometrics Bulletin*, vol. 1, no. 6, pp. 80-83, 1945.

Khaled Harrar was born on February 21th of 1975 in Algiers/Algeria. He received his Engineering degree in Electronic in 1997 from University of science and technology Houari Boumediene (USTHB) of Algiers. A Magister diploma in Electronic in 2001 from the USTHB, and in February 2014 he received his PhD degree from National polytechnical school (ENP) Algiers. He is a member of LSC laboratory, and also a reviewer in an international journal. He is an associate Professor at M'hamed Bougara Boumerdes University since 2004. His research interest concerns signal and image processing including complex texture characterizing by fractal analysis, fractional Brownian motion models, and other approaches based on SVM and neural network technique, for classification, computer aided detection and diagnosis in medical applications. Dr. Harrar has made valuable contribution to research in bone texture characterization and has a number of publications to his credit in International Journals of high repute.

Rachid Jennane is a full Professor of image processing at the University of Orleans (France) where he is affiliated to the I3MTO Laboratory. He received the Ph. D. degree in electrical engineering from the University of Orleans (France) in 1995. His Ph. D. concerned fractal modelling of textures with an application to bone microarchitecture analysis. He has been the principle investigator of several research projects in the image & signal processing areas. His current research interests include the processing of 2D/3D/nD medical images. Especially, porous media and textured images. Since 2006, he is titular of Premium for Scientific Excellence of the Ministry of Research. Pr. Jennane also spent the academic year 1998 as a visiting researcher at the Electrical Engineering Department of the University of Rhode Island (USA). He served as a reviewer for major conferences and journals in the field of image analysis and pattern recognition (Mathematical Reviews, Medical Physics, IEEE-TMI, etc.). He is also a member of the IEEE Society. In 2014, he organized with the support of the International Society for Biomedical Imaging (IEEE-ISBI) the TCB-Challenge (Texture Characterization of Bone radiograph images for the osteoporosis diagnosis). In 2015, he is the General Chair of the international IEEE-IPTA Conference.

