Trabecular Texture Analysis Using Fractal Metrics for Bone Fragility Assessment

Khaled Harrar, Rachid Jennane

Abstract—The purpose of this study is the discrimination of 28 postmenopausal with osteoporotic femoral fractures from an age-matched control group of 28 women using texture analysis based on fractals. Two pre-processing approaches are applied on radiographic images; these techniques are compared to highlight the choice of the pre-processing method. Furthermore, the values of the fractal dimension are compared to those of the fractal signature in terms of the classification of the two populations. In a second analysis, the BMD measure at proximal femur was compared to the fractal analysis, the latter, which is a non-invasive technique, allowed a better discrimination; the results confirm that the fractal analysis of texture on calcaneus radiographs is able to discriminate osteoporotic patients with femoral fracture from controls. This discrimination was efficient compared to that obtained by BMD alone. It was also present in comparing subgroups with overlapping values of BMD.

Keywords—Osteoporosis, fractal dimension, fractal signature, bone mineral density.

I. INTRODUCTION

OSTEOPOROSIS is a disease characterized by a decline in rigidity and mechanical stability of bone, leading to high risk in fracture. The most common method of assessing bone strength is monitoring the bone mass by the bone mineral density (BMD) using quantitative computed tomography (QCT), dual energy X-ray absorptiometry (DXA), and ultrasonography. The role of trabecular bone structure has been increasingly been recognized as significant contributory factor [1], [2], however, the invasive character of these techniques limits their use in large series of patients. For this reason the medical image processing remedies to this problem.

The objective of this study is to develop a screening tool for early detection of osteoporosis in radiographic images based on texture analysis methods using fractal metrics. One of the simplest approaches for describing visual texture is to use moments of the gray-level image histogram, i.e. mean and variance. However, this analysis is somewhat limited, since spatial organization or periodicity information is not provided [3], [4]. Second-order metrics such as fractal dimension and fractal signature are able to characterize bone textures and provide information about the degree of "roughness "of any structure [5], [6].

In recent years, fractal analysis of plain radiographs has been employed to assess the trabecular structure, but almost all these studies have been focused on the fractal dimension evaluation by different approaches (variance method, surface area, Fourier transformation….), and just few works have been done on the fractal signature analysis. The aim of the present work is to discriminate osteoporotic group of patients from a control group based on the fractal signature method, and to compare its results to those of the fractal dimension method using two kind of pre-processing approaches. Results of the fractal dimension were also compared to those of the bone mineral density. This study was also conducted to classify subgroups of osteoporotic cases and controls with overlapping BMD values, to demonstrate the performance of our approach in discriminating between these groups and evaluate the effects of age.

This paper is organized as follows, in Section II; the image acquisition technique is introduced, and the pre-processing approaches are detailed. Results and discussion are presented in Sections IV and V respectively. Section VII draws some conclusions.

II. MATERIAL AND METHODS

A. Image Acquisition

Twenty eight postmenopausal women with osteoporotic femur fractures (65 ± 8.22 years) and an age-matched control group of 28 women (65 ± 8.22 years) have been recruited. The fractal analysis was compared with the femoral bone mineral density analysis. Bone density was measured for all the patients by dual-energy X-ray absorptiometry (DXA; Hologic QDR 1000/W; Hologic, Waltham, MA). The manufacturer recommended to standardize the analysis procedure of the hip and was performed on all patients and controls. The Bone Mineral density (BMD) at the proximal femur were assessed and expressed in grams per square centimetre [7].

The radiographic images were taken following a highly standardized procedure; they are obtained on a Kodak Min R screen-film system [8]. The calcanei were placed in contact with the film; the distance of 1 m was fixed between the X-ray focal source and the film. A 48 kV voltage of the X-ray tube is used and exposure parameters were fixed at 18 mA-s for a time of 0.08 s. The region of interest (ROI) on the radiographic images was located in the trabecular bone at the tuber calcanei, and defined by anatomic marks. The ROI was digitized with a CCD camera to the format 256 x 256 pixels, pixel size being 105 μm (Fig. 1).

B. Image Pre-Processing

In the present study, two pre-processing approaches are used. The first one is applied to extract the bone. The second

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type is used for accessing the bone trabecular network. The aim of these two methods is to highlight the importance of the choice of the pre-processing method providing the most accurate results. The image pre-processing provides a binary image to separate the bone from the marrow.

1. Bone Extraction

To improve the image's quality and get the bone extraction, the clearest regions representing the bone and the darkest regions representing the marrow space are highlighted. To extract the bone, the median filter [3 x 3] was applied to the gray-level intensity images to remove impulse noise, thereafter, the dynamics expansion of the images is useful since the pixels are unevenly distributed over all pixel and this expansion ensures even distribution of gray-levels with respect to all pixels. Finally, the bone's extraction was obtained by thresholding the filtered image using Otsu's method [9]; this last uses the histogram intensities to provide a binary image from a gray-level image (Fig. 2).


(a)
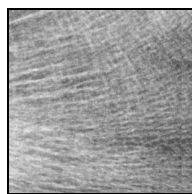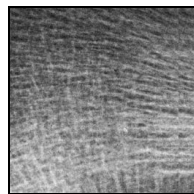
(b)   (c)

Fig. 1 Texture images, (a) Typical radiograph of calcaneus with the ROI, (b) control case and (c) an osteoporotic patient (of the calcaneus after the ROI)

The algorithm uses two classes of pixels to threshold the image (e.g. foreground and background), and then estimates the optimum threshold separating the two classes so that their combined spread (intra-class variance) is minimal.
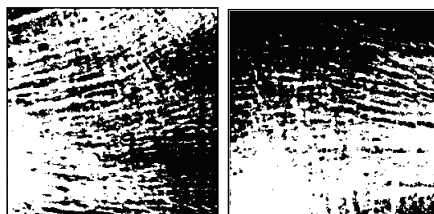

(a)   (b)

Fig. 2 Bone extraction using Otsu's thresholding method, (a) Control case, (b) Osteoporotic patient

2. Trabecular Segmentation

As for the bone extraction, the median filter and the dynamics expansion of the images are used. For the trabecular segmentation process, an edge detection (corresponding to trabeculae) using a laplacian of gaussian (Log) filter is used [10], [11], this segmentation permit to separate the bone trabecular from bone marrow (Fig. 3). The Log filter includes both a smoothing filter, which convolutes the image by a gaussian filter and a 2nd order derivative filter. The purpose of this combined filter addresses the size of the smoothing window but also the variance of the convolutive gaussian. The Otsu's method which is used provides a binary image in which the dark regions represent the bone marrow and the light regions the trabeculae. Finally, an additional pruning step was applied to the resulting image based on removing the residual small size artefacts (< 4 pixels).
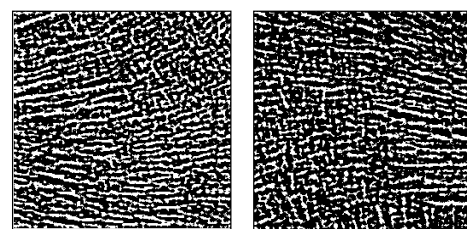
(a)   (b)

Fig. 3 Trabecular segmentation using both LOG ([6x6] and $\sigma = 0,5$) and Otsu's methods. (a) Control case, (b) Osteoporotic patient.

III. FRACTAL ANALYSIS

A. Fractal Dimension

According to the definition of Mandelbrot [12], a fractal is a rough or fragmented object that can be subdivided into parts, each of which is (at least approximately) a reduced-size copy of the whole. Mathematically, a fractal is a set of points where fractal dimension is greater than its topological dimension. Fractals are everywhere in nature: the distribution of galaxies at large scales, the shape of mountains, rocks, lightning bolts, snowflakes, river networks, coastlines, clouds, trees, mammalian blood vessels, trabecular bone network, bronchi in the lungs, etc. The most useful achievement provided by the introduction of fractals is to consider seriously and quantitatively complex irregular structures.
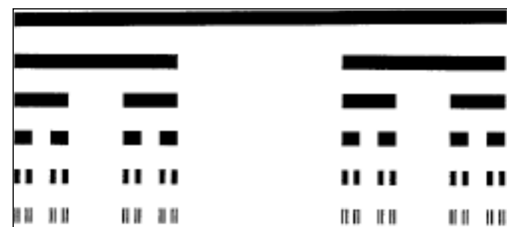

Fig. 4 The initial unit interval and the first five iterations of the construction of the triadic Cantor set are shown from the top to bottom

Fig. 4 shows the topological dimension of the Cantor set. This dimension is $d_t = 0$ since its total measure (length) is zero. This notion of dimension is not very useful since it does not distinguish between this complex set and a single point, which also has a vanishing topological dimension (Fig. 4). To cope with this limitation, scientists have introduced different concepts of dimensions for quantifying such sets. The dimension that generalizes the topological dimension is called fractal dimension defined as:

$$D_c = \lim_{n \to \infty} \frac{\ln N_n}{\ln(1/\varepsilon_n)} \qquad (1)$$

The fractal dimension D_c quantifies the rate at which the number N_n of observable elements change as the resolution $1/\varepsilon_n$ increases.

One of the widely used methods to calculate fractal dimension is the Box counting method, its widespread use is due mainly to its ease of calculation and well adapted to binary images. The idea is to cover the object S with sets of diameter ε. Call N_ε the number of such sets needed to cover S. The box dimension is then [13]:

$$D_b(S) = \lim_{\varepsilon \to 0} \frac{\ln N_\varepsilon}{-\ln(\varepsilon)} \qquad (2)$$

if the limit converges (otherwise replace lim by lim inf or lim sup, respectively the lower and upper box counting dimensions). The box dimension is therefore the power law behaviour of the measurement of the object at scale ε. The number of sets that can cover S is of order $\varepsilon^{-D_b(S)}$. The previous definition remains the same if for N_ε we consider the smallest number of cubes of diameter ε that can cover S [14], hence the name box counting dimension. To obtain an estimate of D_b(S), it suffices to plot ln N_ε versus ln ε. The estimate by the least squares method of the slope of the group of dots (-ln (ε), ln (N (ε))), gives the estimate of fractal dimension.

B. Fractal Signature

Conventional radiographs are used due to their good resolution, they can show the fine detailed structural organization of bones and this can be quantified by fractal signature. Fractal analysis quantifies the roughness and complexity of structures within an image. The scientists consider self-similar images as "fractal" and have a fractal dimension (FD) associated with them [15], [16]. The "fractal signature" of an image quantifies the alteration in the fractal dimension of the structure, and the size(s) at which those changes have occurred [17]. The fractal dimension of cancellous bone assesses the structures of the tissue, determined by number of trabeculae, spacing and cross-connectivity [18]. Unlike other methods that calculate a mean fractal dimension from the overall appearance of cancellous bone [7], the fractal signature analysis techniques measures the fractal dimension separately for vertical and horizontal trabeculae over a range of scales corresponding to a range of trabecular widths, identified as the "fractal signature" [19], [20].

To determine the fractal dimension, the slope of the line $Log(f(\varepsilon)) = f\{Log(\varepsilon)\}$ is calculated. To find this slope, the modeling of set of points $(Log(\varepsilon), Log(f(\varepsilon)))$ by a line using least squares method is used. The local slopes for two successive values of ε represent the fractal signature $S(\varepsilon)$ of the curve defined by:

$$S(\varepsilon) = \frac{Log(f(\varepsilon+1)) - Log(f(\varepsilon))}{Log(\varepsilon+1) - Log(\varepsilon)} \qquad (3)$$

The fractal signature is function of the ε scale analysis and thus proportional to the number of elements of size ε contained in the image. For values of ε far above the average size of texture elements, the surface roughness is not perceptible anymore.

IV. RESULTS

In what follows we present the curves of the fractal analysis applied to the images of the two subjects (control and osteoporotic) whose images were pre-processed in two different ways in order to compare the results, however, the results of all the subjects will be illustrated in Figs. 9-11 and in Table I.
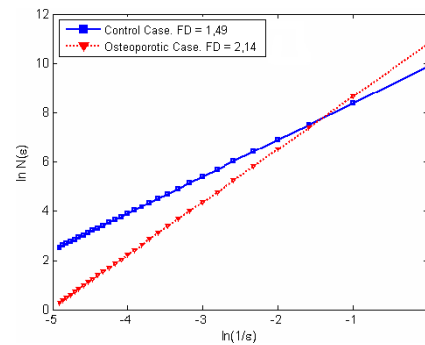

Fig. 5 Fractal dimension calculation, using the box counting method applied to the bone images extraction

Fig. 5 illustrates the log-log plot to estimate the fractal dimension by the box counting method, the high value of the fractal dimension is due to the effect of the fractured bone which corresponds to the patient's osteoporotic image (dashed red line) where a high demineralization is found. In comparison, a low value of fractal dimension is seen in control case (continuous blue line).

The group of dots shown in Fig. 6 represents the application of the least square regression. The fractal dimension calculated by the box counting method is approximately the same for both trabecular segmented images (osteoporotic patient and control case), this reveals the importance of the pre-processing step, contrary to the previous pre-processing (bone extraction), the fractal dimension's values were different for both images.

The number of box on different scales is represented in Figs. 5 and 6. The use of fractal dimension is to give an idea about the irregularity of the bone images, which gives an

indirect information about the porosity. A high value of the fractal dimension is noticed for an osteoporotic bone.
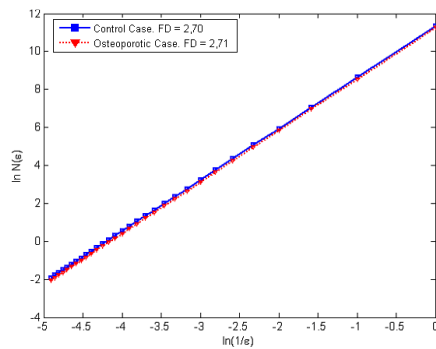

Fig. 6 Fractal dimension calculation, using the box counting method applied to the trabecular images segmentation
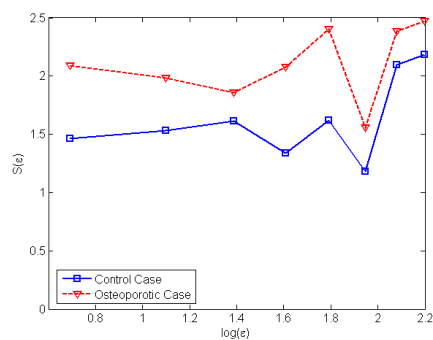

Fig. 7 Fractal signature for the segmented bone images

Line graph in Fig. 7 shows the fractal signature applied to segmented bone images, no overlapping in the curves for both patients is noticed, osteoporotic patient's image (dashed red line) and control case's image (continuous blue line); the fractal signature shows the change in "roughness" with alterations in spatial scale.

The results of the fractal signature applied to the trabecular segmentation images are worse than those applied to the images of the bone extraction, in fact, there is a little overlapping of fractal signatures for these images, at certain scales, the fractal signature is high in osteoporotic patients, however, in other scales it's greater in control cases (Fig. 8). When the pattern of a structure has altered at a particular size or sizes so as to be no longer selfsimilar, the "fractal signature" of its image quantifies the alteration in the fractal dimension of the structure, and the size(s) at which those changes have occurred (Fig. 8).

Fig. 9 shows the rates of higher BMD in control cases, proof of more rigid bone structure. In osteoporotic patients low values of BMD were found, caused by bone demineralization amongst other factors, the latter is influenced by age. An overlapping of BMD in some osteoporotic patients and control cases, are noticed; this drove the researchers to change the definition of the osteoporosis, which was only based on the calculation of BMD, the diagnosis of the osteoporosis becomes complicated. The calculation of the

bone mineral density is a good indicator of the osteoporosis, but not sufficient. Indeed, other factors influence bone strength, this includes the bone turnover rate, bone microarchitecture, bone mass distribution, microlesion accumulation, bone crystal quality, collagen fiber quality, the degree of mineralization, and trabecular microarchitecture [21].
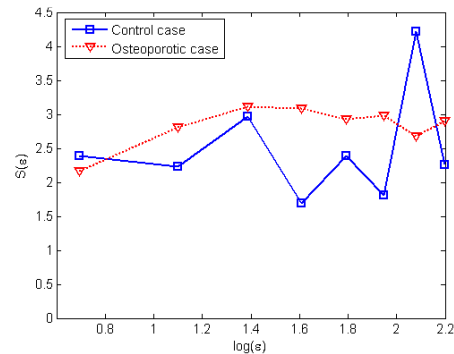

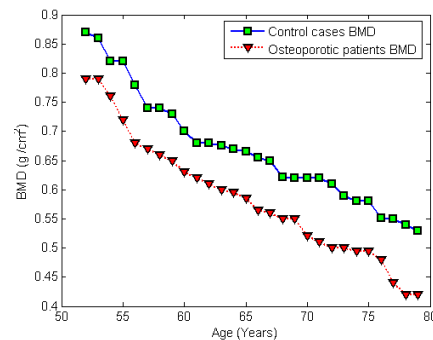Fig. 8 Fractal signature for the trabecular segmentation

Fig. 9 The two groups BMD, osteoporotic patients (dashed red line) and controls (continuous blue line)

The application of Fractal dimension shows a better result in discriminating osteoporotic patients from control cases, a negligible overlapping occurs (Figs. 10 and 11), unlike the BMD values where an important overlapping between these two groups is noticed (Figs. 9 and 11).
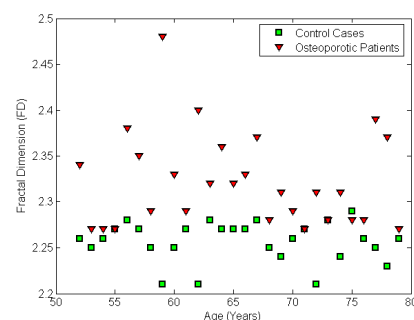

Fig. 10 Representation of the fractal dimensions for all patients (red) and control cases (green)
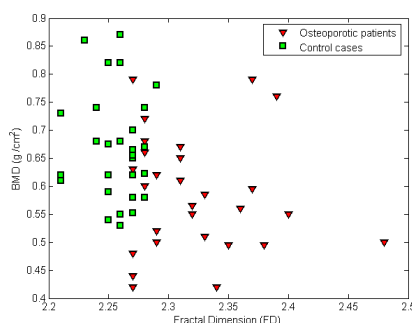
Fig. 11 The bone mineral density versus the fractal dimension

TABLE I
FEATURES ± SD OF OSTEOPOROTIC PATIENTS AND CONTROL CASES

Features	Control cases ± SD	Osteoporotic patients ± SD
Number	28	28
Age (Years)	65 ± 8.22	65 ± 8.22
Weight (kg)	65.5 ± 12.2	64.5 ± 10.6
Height (cm)	161 ± 2	160 ± 1
BMD (g/cm^2)	0.669± 0.09	0.584 ± 0.104
FD	2.25 ± 0.02	2.32 ± 0.05
FS	2.02 ± 0.35	2.51 ± 0.31

The mean value ± SD of age, weight, height, BMD, fractal dimension and fractal signature of control cases and osteoporotic patients are given in Table I. The fractal dimension and fractal signature values are greater for the osteoporotic patients due to high porosity of the bone tissue, inversely for the BMD, where the value is lower in this case.

V. DISCUSSION

In this study, we highlighted the usefulness of the pre-processing step at first with its importance expressed in the results of fractal dimension and the fractal signature applied to radiographic images (Figs. 5-8). The first pre-processing of the bone extraction in which a filtering and a thresholding were applied with Otsu's method gave better results than the second pre-processing approche using the trabecular segmentation in which a Laplacian of Gaussian filter was added (Figs. 5 and 6). The use of this filter provide important changes in the results of the fractal analysis (Fig. 6); in fact, this second pre-processing is well suitable for the bone trabeculae detection in order to characterize the bone architecture using other methods such as histomorphometry (Fig. 3). Furthermore, texture analysis of radiographic images using fractal signature solves the limits of the fractal dimension. Indeed, the latter provides information about the global aspect of a texture; in one hand the fractal signature gave more information on roughness of the textured images over a range of scales (local aspect). In the other hand, it allowed better discrimination of the osteoporotic patients from the healthy cases whatever the selected pre-processing (Fig. 7), unlike the fractal dimension which is confused for these two groups in the case of the second pre-processing method (Fig. 6).

During aging bone structure, this undergoes architectural changes due to osteoporosis caused by bone demineralization

amongst other factors (Fig. 9); in fact the control cases (healthy) had higher rates of BMD than the subjects with osteoporosis, however, the BMD alone is not sufficient to predict osteoporosis. Actually, there is an overlapping of BMD rates in subjects with and without osteoporosis, in other words, in subjects of different ages, same value of BMD can be seen, and vice versa, for two subjects of the same age different BMD rates can be found. The combination of these two parameters allows better discrimination of osteoporotic patients from healthy subjects. To solve this problem, the fractal analysis brings a solution, in fact, in Fig. 10, on the fractal dimensions axis there is a negligible overlapping, which proves a better discrimination of the two groups, contrary to the BMD rates axis where an important overlapping of the two groups is found (Fig. 9).

Previous works have shown that fractal parameters can be evaluated on histological sections, μCT images, and MRI scans [21]. As part of a larger study, the Osteodent project, [22] 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. Another work conducted by [23], they quantified the anisotropy in femoral trabecular bone using CT images.

Our study related to the comparison of the results of the fractal analysis (fractal dimension and fractal signature), these two methods were applied to radiographic images of calcanei, which underwent two types of pre-processings, the goal of all that is the discrimination of the groups and sub-groups of subjects (control and osteoporotic cases), we showed that the fractal analysis discriminates the two subjects better compared to the BMD alone.

We have used conventional radiographs for their high resolution; radiological texture analysis can be readily used in vast populations. The results are reproducible and correlated with biomechanical properties and with a number of histological characteristics [21], [24].

A texture analysis needs an optimal quality of radiographic image. It is very important to standardize all the steps from the acquisition to the digitalization. Each parameter must be fixed to avoid the variation in result: positioning of the ROI, use the same source, the distance focal source, intensity and voltage, time exposure, radiologic film, digitalization system…

The contributions of our study can be summarized as following:
- The importance of pre-processing step.
- The comparison between the fractal dimension and the fractal signature applied to radiographic images.
- The discrimination of subgroups with overlapping values of BMD.

Further studies will be necessary to provide more information on the precise relationship between the BMD, the microarchitecture and the fractal analysis, in order to understand the exact mechanisms leading to bone fragility and find new and more effective therapeutic strategies to face consequences of osteoporosis and other metabolic bone diseases.

VII. CONCLUSION

The significant increase in fractal dimension of structures in the radiographic images was consistent with changes associated with early osteoporosis. These changes would result in an increase in the number and cross-connectivity of fine trabecular structures and also a higher fractal signature value due to the increased appearance of 'roughness' of the trabecular organization. Fractal analysis quantified significant difference in bone structure whereas DXA detected no significant difference in BMD for the same ROIs. Therefore, for different pre-processing, fractal signature is a more sensitive method of measuring differences between osteoporotic and non-osteoporotic cancellous bone than fractal dimension. The techniques used in this study are non-invasive and can provide structural information about bone, beyond simple bone densitometry, the overlapping involved in measuring BMD is resolved by the fractal analysis. The Fractal signature relates the "fractal" dimension with scale by an extension of the fractal dimension philosophy. Texturally, the Fractal signature is a measure of information at different image scales, and thus the strength and spatial size(s) of texture. Fractal fractional dimensions and signatures not only characterize the object's topology but also, being related to their properties of dynamic systems.

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