EVALUATION OF RADIOGRAPHIC TEXTURE ANALYSIS FOR THE CHARACTERISATION OF 3D BONE MICRO-ARCHITECTURE : INFLUENCE OF SPATIAL RESOLUTION

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Abstract : Although the diagnosis of osteoporosis is mainly based on Dual X-ray Absorptiometry, it has been shown that trabecular bone micro-architecture is also an important factor in regards to fracture risk. In vivo, techniques based on high-resolution x-ray radiography associated to texture analysis have been proposed to investigate bone micro-architecture, but their relevance for giving pertinent 3D information is unclear. 25 calcanei bone samples including the cortical shells (diameter: 14 mm, height : 30 to 40 mm) were imaged using 3D-synchrotron x-ray microtomography at the ESRF (Grenoble). The 3D reconstructed images with a cubic voxel size of 15 µm were further used for quantifying three-dimensional trabecular bone micro-architecture, and for simulating realistic x-ray radiographs at different spatial resolutions. The resulting x-ray radiographs were then analyzed using a variety of texture analysis methods (co-occurrence, spectrum, fractal, morphological gradient …). The correlation of these parameters to 3D micro-architecture parameters and their variation with spatial resolution were examined. Our analysis showed how to adjust parameter of particular method according to the resolution. Typical results show that "Trabecular Space" (Tb.Sp) is correlated with Co-occurrence matrix features with |R|=0.76 even at 200 microns, Trabecular Thickness (Tb.Th) is correlated with Fractal Dimension feature with |R|=0.88 at 50 microns and |R|=0.73 at 150 microns.

Introduction

Osteoporosis is a disease in which the density and the quality of bone are reduced, leading to weakness of the skeleton and increased risk of fracture, particularly of the spine, wrist, hip, pelvis and upper arm. Osteoporosis and associated fractures are an important cause of mortality and morbidity. In many affected people, bone loss is gradual and without warning signs until the disease is advanced.

The diagnosis of osteoporosis is based on measurement of the bone mineral density (BMD). BMD measures the amount of calcium in regions of the bones. Most methods for measuring BMD (also called bone densitometry) are fast, non-invasive, painless, available on an outpatient basis and have possibility to diagnose 70% of the cases.

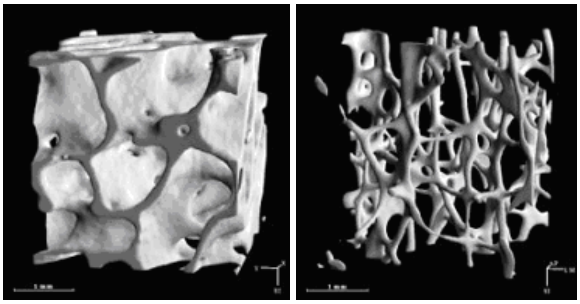

Figure 1: Healthy bone (left) and bone affected by osteoporosis (right)

Drawback of BMD measure is that it gives little information on quality of the bone in terms of micro-architecture. Differences in bone micro-architecture between individuals, who have equivalent BMD, could be crucial factor for determining mechanical resistance of bone. Unfortunately, characterization of bone micro-architecture is difficult to obtain non-invasively. It has been proposed to observe bone micro-architecture as a texture. The radiographic process reduces the three-dimensional structure of the bone in a two-dimensional image of texture. Texture analysis consists in extraction of parameters characterizing the arrangements of the more or less regular patterns that constitute image. Several teams proposed to use texture analysis on such radiographs to extract information on bone micro-architecture [1, 2, 3]. We propose in this study to evaluate the relevance of the textural features to explain the micro-architecture according to the image resolution and the level of noise in image. The study was performed on simulated radiographic images without noise and by

ISSN: 1727-1983

adding 5% of noise and at different spatial resolution, with pixel size in the radiography going between 50 and 200 microns.

Material and methods

Bone samples : Twenty-five calcanei and eight femoral necks were taken from human corps at the Nîmes CHU Hospital. In each piece, a cylindrical core (diameter: 14mm) was cut out in the mediallateral direction using an electric drill corer. The bone samples including two cortical shells had a height varying between 30 and 40mm and were preserved in formalin. All the samples came from the patients whose death was not due to an infection or a contagious disease. The samples were then glued vertically on a Plexiglas holder in order to be imaged using micro tomography (micro-CT).

3D imaging : All samples were imaged using synchrotron radiation micro-CT at European Synchrotron Research Facility (ESRF). To get 15mm "Field of View", 15µm pixel size and a 2048 × 2048 CCD camera in binning mode (image size: 1024 × 1024) were used. For each scan, 900 radiographs (projection images) were acquired, for 180° object rotation that corresponds to an angular step of 0.2°. For each scan, a 3D volume was reconstructed from 900 tomographic projections using 3D filtered back projection algorithm.
In order to characterize 3D bone micro-architecture, it was necessary to select a trabecular bone "Volume of Interest" (VOI) within each sample.

Figure 2: Reconstructed image of bone sample

Quantification of 3D bone micro-architecture : 5 quantitative parameters were extracted from the selected VOIs: BV/TV (Bone Volume/Total Volume), BS/BV (Bone Surface/Bone Volume), TbTh (Trabecular thickness), TbSp (Trabecular Space) and TbN (Trabecular Number). A direct or model independent method requiring no a priori assumption on the geometry of bone structure was proposed to calculate the TbTh and TbSp.

Simulation of radiographic images : The entire bone sample images including the two cortical shells were used to simulate radiographs of the samples. A flexible radiograph simulator, developed by LETI, which enables choosing various experimental conditions, was used. It allows to define the characteristics of the material to be tested (structure of bone in our case), the radiographic chain (x-ray source spectrum, size of pixel on detector, detector modulation transfer function, noise, ...), as well as geometrical characteristics such as projection angles, source to detector distance, and sample to source distance. A simulation requires several parameters of adjustments: parameters of geometry (to define the position of volume in front of the detector, the steps of samplings of the lines and columns), and of the parameters of simulation conditions (medium, noise, duration of the experiment ...). The software operated on 8 Gbytes RAM computer using the following conditions :

- 128×128 elements detector (size of element radiographs)
- pixel size on detector: 50µm × 50µm
- source-detector distance 1300mm
- sample-source distance 1180mm
- filtered 75kV
- no noise.

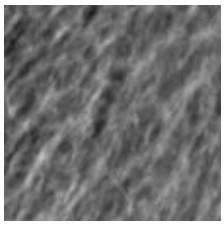

Figure 3: Simulated radiographic image of a bone sample

Fig. 3 is showing simulated radiograph of same bone sample with different projection angles. Some differences can be observed in the texture in these two images of the same sample.

Image resizing : As noted, detector size was set to 50µm. To simulate radiographs on different detector size, pictures were resampled to decreased number of pixels, with basic bilinear interpolation. Bilinear Interpolation determines the value of a new pixel based on a weighted average of the 4 pixels in the nearest 2 × 2 neighbourhood of the pixel in the original image. The averaging has an anti-aliasing effect and therefore produces relatively smooth edges.
From Fig. 4 we see that with each picture size reduction fine details of picture are lost.

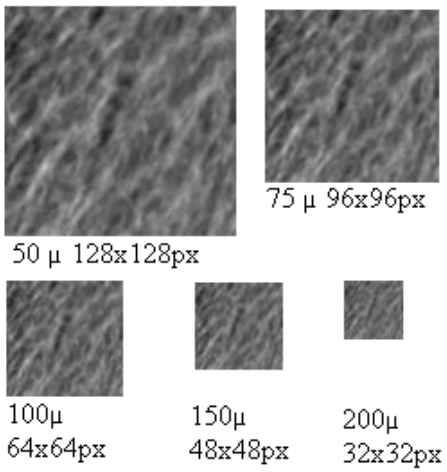

Figure 4: Bone samples at different detector size

ISSN: 1727-1983

Adding noise to image : It was previously noted that the images are simulated without noise. But in reality digital images are corrupted by noise during image acquisition. To make simulated radiography images more realistic, a zero-mean gaussian noise was added to the original images.

Texture analysis : An image texture is described by the number and types of its primitives and their spatial organization or layout. The spatial organization may be random or have some basic building blocks. Image texture can be qualitatively evaluated as having one or more of the properties of fineness, coarseness, smoothness, granulation, randomness, lineation or as being mottled, irregular. Each of these qualities translates into some property of the grey level primitives and the spatial interaction between them.
Analysis of texture is based on mathematical techniques and consists in calculating a number of parameters supposed to characterize the texture under study. Ehrich and Foith [4] divided textural analysis as:
1. Given a textural region, determine to which of finite number of classes the region belongs.
2. Given a textural region, determine a description or model for it.
3. Given an image having many textured areas, determine the boundaries between the differently textured regions.
Issue 1 has to do with the pattern recognition task of textural feature extraction. Issue 2 has to do with generative models of texture. Issue 3 uses knowledge from issue 1 and 2 to perform a texture segmentation of an image.

Methods for texture analysis : Reed [5] divided textural analysis methods in four groups:
• structural or deterministic methods in which a texture is described by its primitive(s) and the rules governing the distribution of primitives (well adapted to ordered textures)
• statistical methods which provide relationships between a pixel and its neighbours (well adapted to irregular textures or textures without apparent regularity). They include co-occurrence matrix [6], run length matrix methods, neighbourhood matrices, ...
• transformation methods which extract parameters in the image represented in a "transformed" domain where the information can be highlighted more easily (for instance of Fourier transform, wavelet transform or Gabor filters, ...).
• model-based methods which identify parameters of a mathematical model of the texture (for instance fractals, auto-regression, ...).
It is not possible in the frame of this paper to describe in details all the texture analysis methods and the textural parameters used in the study. The presented results involve mainly 3 methods : Co-occurrence matrix method [6], Fractal dimension [7, 8] and Gradient Morphology method [9]. The reader can refer to these references for a description of the methods.

Results

The range of micro-architecture parameters was in agreement with previous studies and was rather large suggesting that the population was representative.
Simple correlation: The first experiment consisted in calculating the correlation between textural features and morphological features. A very large number of textural features were calculated (352) on each radiographic image at the full resolution (50 microns) and without noise. We observed that for each morphological feature, a good correlation can be found with textural features (higher than 0.65). One example is given on figure 5. This figure presents the simple linear regression graphs obtained between the Fractal dimension texture parameter (method SemiVariance 1 3) and the morphometric parameter TbTh* for the series of calcanei.

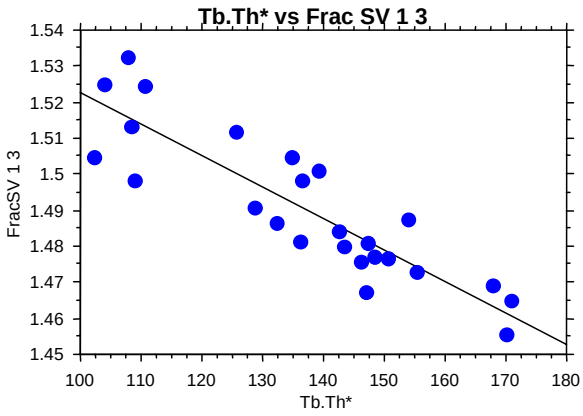

Figure 5. Linear regressions between the Fractal dimension texture parameter and the morphometric parameter Tb.Th*.

The correlation coefficient of the two parameters is R=0.88. Approximately the same graphs for every morphometric features can be obtained.
In view to evaluate the relevance of the textural feature to explain the micro-architecture, noise was added to the simulated images and at different resolutions (from 50 microns to 200 microns per pixel). The results are summarized in table 1 for a selection of textural features.
It shows that morphometric features TbSp and TbN can be described correctly by textural feature *Mean in X* calculated by co-occurrence matrix method. The correlation is R=0.76 at 50µ and is quite stable for different resolution and at different noise level.
We should also point out, how to adjust the input parameters for different resolution. Our images were of size 128x128 pixels at 50µ sensor size. When we change the sensor size to 100µ the image size decreases to 64x64 pixels. This means that if the sensor size increases, the image resolution, and the image size decrease in the same way. Spatial operators

ISSN: 1727-1983

used to calculate the co-occurrence matrix and the textural parameters should be adjusted properly. When the image size is reduced (bigger sensor size), displacement vector of spatial operator should be reduced bay the same factor.

Table 1 also shows that Fractal dimension method based on Power Spectrum Density is much more robust according to noise, than the Fractal method based on calculating SemiVariance. We see that textural parameter calculated by Fractal dimension method SemiVariance drops from R=0.88 at 0% of noise to R=0.39 at 5% of noise. On the other hand textural parameter calculated by Fractal dimension method based on Power Spectrum Density exhibits a correlation R=0.82 at 100µ and noise level 0% and R=0.7 at 5%. The correlation decreases but not as much as for textural parameter Fractal dimension calculated by method SemiVariance. The Gradient Morphology method is showing promising at 50µ sensor size. Correlation with morphometric parameters Tb,Th* and BS/BV is well over 0.85. But with bigger sensor size (smaller images), the correlation of textural parameter with morphometric parameters is lost. Also with increasing noise level, the correlation of textural parameters calculated by Gradient Morphology method is decreasing. This can be due to a large sensibility of the method to the adjustment of the spatial parameter used in this method.

Linear model: Table 1 shows that morphometric parameter BV/TV is not highly correlated (R>0.65) with any of the textural parameters. The idea is to try to describe BV/TV with several textural parameters.

Since all textural analysis methods can have a variety of different input parameters, a large number of textural parameters are calculated. From these parameters a linear model for describing morphometric parameters, is build. using multiple regressions. In a first step the method calculates witch textural parameter present the highest correlation with a particular morphological parameter. In the next step, a new parameter is added and the one that contributes the most to correlation is kept. This is repeated several times, according to the number of textural parameter that we want to involve in the model. At each step, we control that the model remains statistically significant (p-value lower than 0.05)

Results are summarized in table 2. The R-squared value and the number n of parameters used in the linear model are indicated. We can see that if 3 textural parameters are used to describe morphometric parameters, R-squared is above 0.65 for each morphologic parameter and at each resolution. The morphometric parameter BV/TV could not be explained with only one textural parameter, but with 3 parameters, R^2=0.873 at 50µ and R^2=0.79 at 200µ. The correlation decreases with resolution but not so fast as in the case of only one textural parameter. Figure 6 shows the predicted value calculated by linear model versus actual morphometric value. This model obtained with one parameter exhibits a high R-squared value. (R^2=0.88). Such a model allows to calculate a good approximation of the actual value of Tb.Th*

For each mophometric feature, a model with a high R-squared value can be build with less than 4 textural

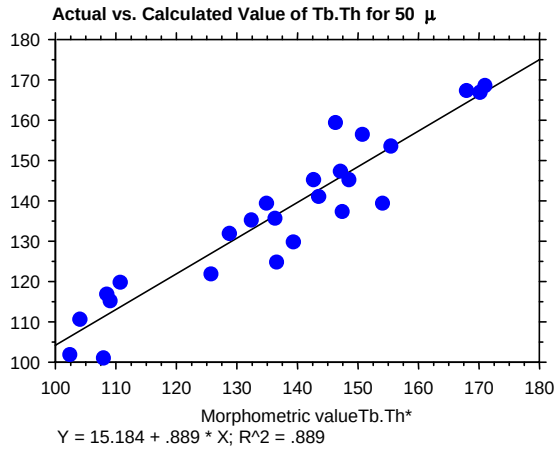

Figure 6 : Predicted values of TbTh* versus actual values using a linear regression model.

features and at a resolution of 100 microns. This means that it can be possible to characterize the micro-architecture of bone from radiographic images obtained with the resolution of commercial devices.

Conclusions

In this study, we attempted to identify 2D texture features calculated from radiographic image of bone to predict 3D micro-architecture. The simple correlation and multiple regression analysis allow to point out some textural features that remain relevant at the lowest resolution. Texture analysis method, such as the well known co-occurrence matrix method can provides relevant features to explain the characteristics of bone. These features can reveal robust to noise alteration or to resolution modification if the spatial operators are adjusted properly

The methodology proposed for evaluating the relationships between 3D micro-architecture and 2D texture parameters may also be used for optimizing the conditions for radiographic imaging.

In future, this approach could be used in combination with DXA to refine osteoporosis diagnosis.

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ISSN: 1727-1983

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Table 1 : Simple correlation coefficient of the 5 morphometric parameters with some textural features for different resolutions (50 to 200µm), without noise (0%) and with 5% of noise

Res. (µ)		Tb.Th*		Tb.Sp*		Tb.N		BV/TV		BS/BV	
		0 %	5 %	0 %	5 %	0 %	5 %	0 %	5 %	0 %	5 %
50	Fractal dimension SV 1 3	0.88	0.39	/	/	/	/	/	/	0.83	0.32
	Gradient Morph DE 7 3	0.92	0.57	/	/	/	/	/	/	0.88	0.51
	Co-occurrence Mean in X 102	/	/	0.76	0.76	0.66	0.66	/	/	/	/
75	Fractal dimension SV 1 3	0.85	0.452	/	/	/	/	/	/	0.74	0.36
	Gradient Morph DE 7 3	0.85	0.617	/	/	/	/	/	/	0.75	0.51
	Co-occurrence Mean in X 76	/	/	0.76	0.76	0.66	0.66	/	/	/	/
100	Fractal dimension SV 1 3	0.79	0.532	/	/	/	/	/	/	0.66	0.43
	Fractal dimension PSD 2 32	0.824	0.7	/	/	/	/	/	/	0.75	0.61
	Co-occurrence Mean in X 47	/	/	0.74	0.74/	0.66	0.66	/	/	/	/
150	Fractal dimension SV 1 3	0.734	0.553	/	/	/	/	/	/	/	/
	Co-occurrence Contrast 8 0	0.66	0.659	/	/	/	/	/	/	/	/
	Co-occurrence Mean in X 38	/	/	0.767	0.767	0.66	0.66	/	/	/	/
200	Co-occurrence Contrast 5 0	0.669	0.660	/	/	/	/	/	/	/	/
	Co-occurrence Mean in X 25	/	/	0.767	0.767	0.66	0.66	/	/	/	/

Table 2 : Multiple regression experiment. The independent variables are the textural features and the dependent variables are the 5 morphometric parameters. Results of R-squared value and number of parameters involved in the model for different image resolutions (50 to 200µm)

Resolution (microns)	Tb.Th*		Tb.Sp*		Tb.N		BV/TV		BS/BV	
	R^2	n	R^2	n	R^2	n	R^2	n	R^2	n
50	0.883	1	0.835	3	0.866	3	0.873	3	0.962	3
75	0.92	3	0.825	3	0.797	3	0.79	3	0.879	3
100	0.88	3	0.87	3	0.77	3	0.79	3	0.85	3
150	0.865	3	0.843	3	0.798	3	0.798	3	0.792	3
200	0.8	3	0.836	3	0.77	3	0.73	3	0.67	3

ISSN: 1727-1983