Texture Analysis for Trabecular Bone X-Ray Images Using Anisotropic Morlet Wavelet and Rényi Entropy

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Abstract. In this paper, we propose a new method based on texture analysis for the early diagnosis of bone disease such as osteoporosis. Our proposed method is based on a combination of four methods. First, bone X-ray images are enhanced using the algorithm of Retinex. Then, the enhanced images are analyzed using the fully anisotropic Morlet wavelet. This step is followed by the quantification of the anisotropy of the images using the Rényi entropy. Finally, the Rényi entropies are used as entries for a neural network. Applied on two different populations composed of osteoporotic (OP) patients and control (CT) subjects, a classification rate of 95% is achieved which provides a good discrimination between OP patients and CT subjects.

1 Introduction

Osteoporosis is considered as a major public health issue [1] due to an increase frequency of fractures of the hip, spine, and wrist. Osteoporosis is characterized by a severe degradation of the bone mass and an alteration of the bone microarchitecture. This problem is currently affecting more than 200 million people worldwide. Epidemiological studies provide a very significant increase in the number of osteoporotic fractures in the coming years [2]. Osteoporosis is clinically assessed by using BMD (Bone Mass Density). Despite the effectiveness of this technique, it does not give information about the microarchitecture of the bone tissue. If BMD is combined to an independent technique that describes the microarchitecture, this might enable a better and precise diagnosis [3] for the prediction of fracture risk. Obviously, it has to be non invasive for the patient, not expensive, reproducible and efficient. The calcaneus (the bone of the heel) is subject to forces of compression and tension produced by the gravity of the human being, making it very suitable for the characterization of the bone mircroarchitecture (Fig.1). For a normal subject, the compression and tensile trabeculae are uniformly distributed . For an osteoporotic subject, the tensile trabeculae may disappear making the structure anisotropic. The modifications

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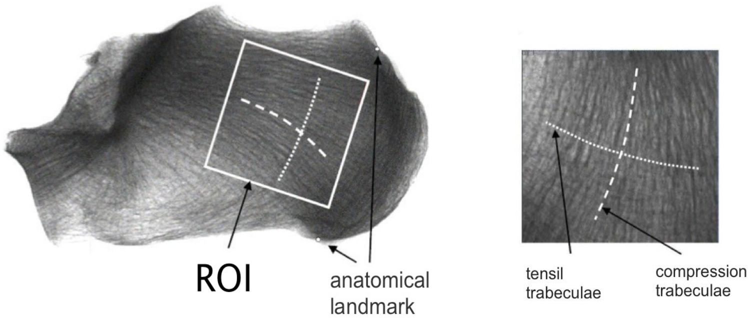


(a) (b)

Fig. 1. (a) A typical radiography of the calcaneus with the Region Of Interest (ROI). (b) 256 × 256 extracted ROI.

of the organization of the trabeculae and their thickness can help evaluating the damage of the bone.

Several studies have attempted to evaluate osteoporosis to characterize the anisotropy of textured images. Sevestre *et al.* [4] developed a morphological study to establish a skeleton of the trabecular bone microarchitecture. Despite their quite interesting results, the tool is very complex to produce.

Many methods of texture analysis have been proposed over the last three decades [5,6]. These methods are evaluated over natural and textured surfaces which are quite distinctive for the human vision system. The texture present in osteoporotic and healthy bone radiographs, however, are visually close to each other, making the discrimination task very challenging. Other methods using fractal analysis for bone texture have been explored [7,8,9]. These methods gave interesting results but are still under investigation for an efficient characterization of bone texture organization. More recently, some of the authors of the present study [10] proposed a new descriptor called 1D LBP (One Dimensional Local Binary Pattern) for bone texture characterization. Results of this study demonstrated the importance of preprocessing the data to improve the classification rates to distinguish between CT and OP subjects. In the same way, Pramudito *et al.* [11] combines the coefficients of the wavelet and the fractal dimension to identify the disease. Their method offers a new perspective to analyze such kind of images.

In this work, we propose a method which enables characterizing the anisotropy of an image using the entropy of Rényi and a fully anisotropic Morlets. The Rényi entropy has shown its effectiveness especially to quantify the anisotropy [12]. The use of a fully anisotropic Morlet enables settling the problem of non-uniform changes.

This paper is organized as follows. Section 2, describes the methods used to characterize trabecular bone data on radiographs. Section 3 presents the experimental results obtained on two different populations composed of osteoporotic patients and control subjects. Finally, some concluding remarks are discussed in section 4.

2 Methods and Materials

Our goal is to study the effect of preprocessing the data of bone radiograph images for the diagnosis of osteoporosis. Different methods are considered. First, images are enhanced. Then, the fully anisotropic Morlet wavelet is used to analyze the images. After computing the two-dimensional histogram, the features of the Rényi entropy are used to distinguish between the two populations(OP and CT). Fig. 2 shows our studied Cases.

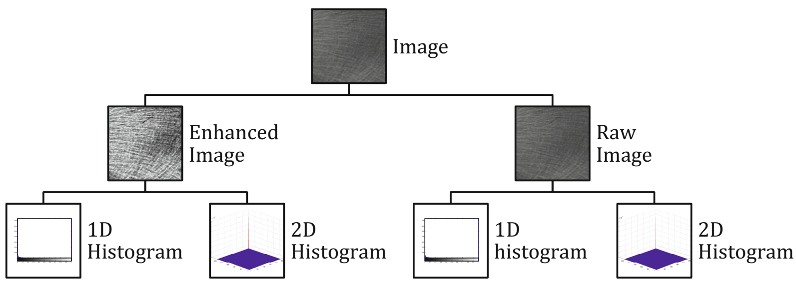


Fig. 2. Global chart of the proposed method

2.1 Preprocessing

To process the different data, first, we have used the Retinex algorithm introduced by Land *et al.* [13]. This method improves the contrast of the images using the reflection of light. There exist several versions of this algorithm and we have used the one defined by Funt *et al.* [14]. To keep the significant information of the trabecular bone patterns, a quantization over fewer gray levels was performed. Only 8 gray levels were kept to provide better and more easily exploitable images that are better suited for bone texture characterization. Figure 3 shows a sample of an enhanced and quantized image of a bone X-ray image.

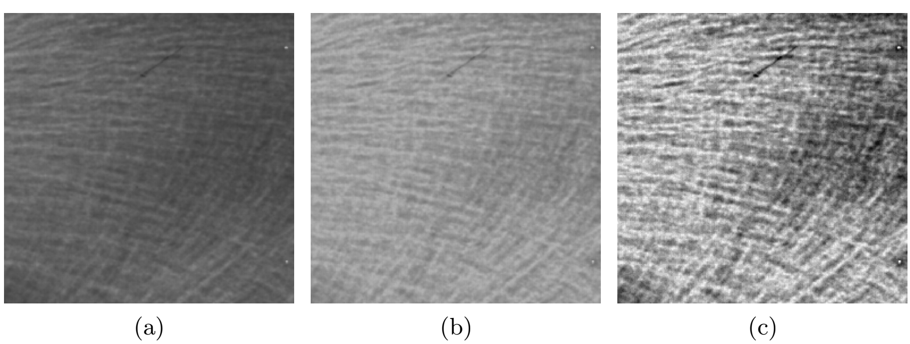


Fig. 3. (a) Original image of a calcaneus radiograph,(b) filtered image by the Retinex algorithm (c) and quantized image over 8 gray levels

2.2 A Fully-Anisotropic Morlet Wavelet

The Morlet wavelet, was formulated by Goupillaud *et al.* [15]. Then, Antoine *et al.*[16] proposed anisotropic Morlet which is given by:

$$\psi(x) = e^{ik_0 \cdot x} e^{-1/2(x.A^T Ax)} \tag{1}$$

where $\mathbf{k_0} = (0, k_0) \geq 5.5$ is a wave vector and $A = diag(L, 1)$ is an anisotropic matrix, "diag" denotes the diagonal matrix and L is the ratio of anisotropy. Kumar *et al.*[17] have controlled the orientation by defining $k_0 = (k_0 cos\theta, k_0 sin\theta)$ where θ is the parameter of orientation. The combination of the methods proposed by Kumar *et al.*[17] and Antoine *et al.*[16] produces an anisotropic and directional wavelet. This wavelet is not fully anisotropic. To solve this problem, Roseanna *et al.* [18] proposed a fully anisotropic Morlet where both the elliptical envelope and the wave vector are rotated through an angle defined by the orientation parameter θ. This wavelet is given by:

$$\psi(x, \theta) = e^{ik_0.Cx} e^{-1/2(Cx.A^T ACx)} \tag{2}$$

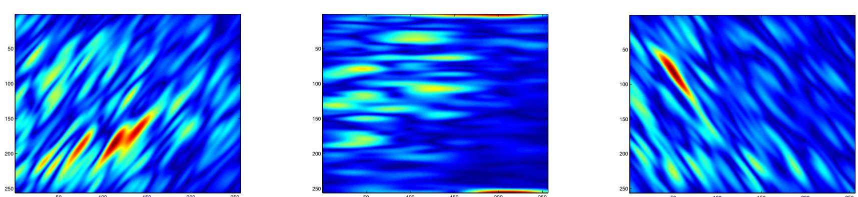
with k_0=$(0, k_0)$, $k_0 \geqslant 5.5$,$A = diag(L, 1)$ and C is a linear transformation defined by:

$$C = \begin{bmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix} \tag{3}$$

So, the Wavelet coefficients are given by the following convolution:

$$W_\psi f(\mathbf{b}, a, \theta) = \frac{\sqrt{L}}{a} \int_{-\infty}^{\infty} f(x) \overline{\psi}\Big(\frac{x - \mathbf{b}}{a}, \theta\Big) dx = \frac{\sqrt{L}}{a} f(\mathbf{b}) * \overline{\psi}(-\mathbf{b}/a, \theta) \tag{4}$$

The exploitation of the fully anisotropic Morlet, enabled us solving the problem of orientation which is caused by the non-uniform changes. Fig. 4 shows a representative example of subband of an image from the database in different orientations.



(a) -45^o degree (b) 0^o degree (c) 45^o degree

Fig. 4. A representative example of a sub-band for a Xray bone image in different orientations with $\mathbf{L} = 0.2$ and $a = 4$

2.3 2D Histogram of Fully-Anisotropic Morlet Wavelet

To characterize the Morlet coefficients we use a two-dimensional (2D) histogram proposed by Sahoo *et al.* [19]. To Compute the 2D histogram for each sub-band, we proceed as follows. First, we calculate the average of the neighborhood for each coefficient. Let $g(x,y)$ be the average value of the neighborhood for the coefficient $f(x,y)$. Thus for a 3×3 neighborhood $g(x,y)$ is calculated as:

$$g(x,y) = \left\lfloor \frac{1}{9} \sum_{a=-1}^{1} \sum_{b=-1}^{1} f(x+a, y+b) \right\rfloor \tag{5}$$

where$\lfloor A \rfloor$denotes the integer part of A. The average value is used for the construction of the normalized 2D histogram as:

$$Hist2D(k,l) = \frac{Prob(g(x,y) = k \cap f(x,y) = l)}{Number\ of\ Pixel} \tag{6}$$

Note that $(\sum_{i=1}^{N} \sum_{j=1}^{M} Hist2D = 1)$ where (M,N) is the size of the 2D histogram. The 2D histogram is used to compute the entropy as explained in the next section.

2.4 Rényi Entropy for 2D Histogram

The Rényi entropy [20] is widely used for the description of anisotropic textures. The Rényi entropy results from the generalization of the Entropy of Shannon. It is an efficient tool which has shown good performances [12]. The Rényi entropy, H_α, of order α ($\alpha \geq 0$, $\alpha \neq 1$) is defined as:

$$H_\alpha(X) = \frac{1}{1-\alpha} \log\left(\sum_{i=1}^{n} p_i^\alpha\right) \tag{7}$$

where p_i represents the probability density of $X = \{x_1 \cdots x_n\}$. In the literature and for most cases, the Rényi entropy refers to case $\alpha = 2$. In our case, the Rényi entropy was used as a feature for the description of each image. To this end, we have used the 2D histogram and the Rényi entropy, $Entro_{2D}$, as follows:

$$Entro_{2D} = \frac{1}{1-\alpha} \log\left(\sum_{i=1}^{N} \sum_{j=1}^{M} Hist2D^\alpha(x,y)\right) \tag{8}$$

where $Hist2D$ is the Histogram 2D of each subband and M is the maximum gray level for the Histogram of sub-band and N is the maximum gray level for the Histogram of average of the same sub-band.

3 Experimental Results

For this study, we considered a population composed of 77 postmenopausal women suffering from osteoporotic vertebral crush fractures and control subjects. Among these subjects, there were 38 control (CT) cases and 39 patients with osteoporotic (OP) fractures. As age has an influence on bone density and on trabecular bone microarchitecture, the control cases were age-matched with the vertebral crush fracture cases.

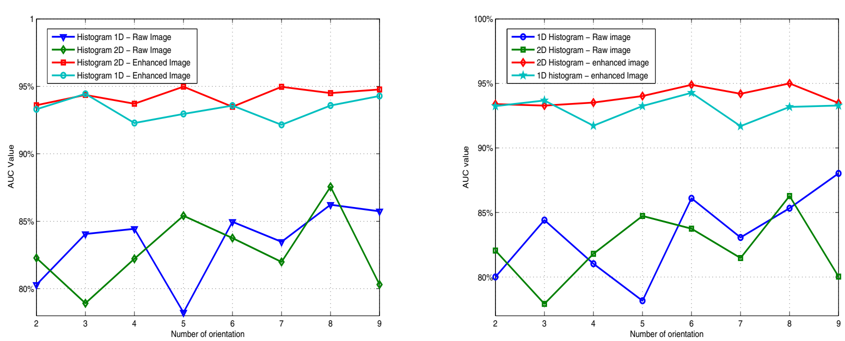
To realize calcaneus X-ray images a standardized procedure was followed. An X-ray clinical equipment was used. Focal-calcaneus distance was set at 1 m. The region of interest (ROI; Fig. 1a) was defined by a physician who marked anatomical markers on the calcaneus images. This way, we ensure that the ROI be acquired in the same area as well as in the same orientation from each bone radiography, since the effect of the orientation on the analysis is part of this study. This ROI of 2.7×2.7 cm^2 was located in a region that contains only trabecular bone. The pixel size was 105 μm.

The preprocessing as well as the orientation of analysis were evaluated. We have also compared the results obtained using either the two-dimensional or the one-dimensional histogram in the Rényi entropy.

Our method is based on a 4-step algorithm. First, the image content is enhanced. Then, each image is analyzed using the fully anisotropic Morlet wavelet in different orientations. Follows, the computation of the 2D histogram on each sub-band. Finally, the entropy from Rényi is estimated using each two-dimensional histogram. Namely, for the orientations, we used a range of $\theta = [-180, -135, -90, -45, 0, 45, 90, 135, 180]$. Thus, for each image, we choose $1 \leqslant N \leqslant 9$ for this range of orientations.

For the parameters of the Morlet wavelet, we chose $L = 0.2$ to take advantage of fully-anisotropique anisotropy [18] . For the scale, we use $\boldsymbol{a} = 4$. Since, the purpose of this paper is take advantage for fully-anisotropic wavelet, the influence of the scales will be considered in a future work.

As a classifier, we used the neural networks with N as the size of the input vector with 30 nodes for the hidden layer and output. For the distribution of the data, we used 50% for learning, 25% for the test and 25% for the validation. Moreover, the Receiver Operating Characteristics curves (ROC) [21] were used



(a) (b)

Fig. 5. AUC values depending on Number of Orientation using the Rényi entropy: (a) OP Class,(b) CT Class for 4 studied Case (Fig.2)

to measure the influence of N on the rate of the classification. All the procedures were executed 100 times and the mean value was retained as a representative result.

Figure 5 shows the evolution of the Area Under Curve (AUC) of the ROC curves while varying the parameter N. Each graph corresponds to one of the proceeded data, raw or enhanced images using either the 1D or 2D histogram. As can be seen on figure 5, the enhancement improves the classification rates. The best classification rate is obtained for the enhanced image using the 2D histogram. $N = 4$ gives a good classification rate and seems to be a good trade off between efficiency and computation time.

4 Conclusion

In this work, we have proposed an original approach based on a fully-anisotropic Morelet and Rényi entropy for texture characterization with an application to bone X-ray images for the diagnosis of bone disease such as osteoporosis. Our technique combining image preprocessing and the entropy shows that it is possible to achieve better classification rates to distinguish between two different populations composed of osteoporotic patients and control subjects. The fully-anisotropic Morlet, helped us estimating non-uniform changes due to anisotropy variations induced by osteoporosis. The Neural Network classifier and the Receiver Operating Characteristics curves were used to distinguish between osteoporotic and control subjects. Combining our technique to Bone Mineral Density we can offer a new perspective for precise studies of bone disease such as osteoporosis.

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