TEXTURE ANALYSIS USING DUAL TREE M-BAND AND RÉNYI ENTROPY. APPLICATION TO OSTEOPOROSIS DIAGNOSIS ON BONE RADIOGRAPHS

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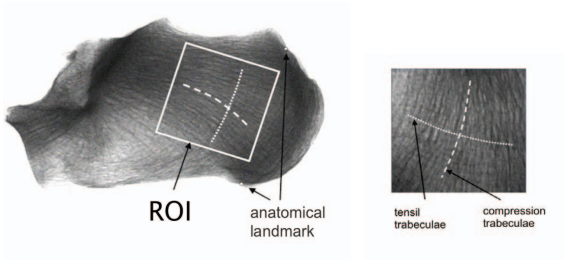
ABSTRACT

In this paper[1],we propose a new method based on texture analysis for trabecular bone disease diagnosis. For this purpose, we present a working model based on a preprocessing step followed by a projection on a 1D oriented axis at a defined angle. First, the dual-tree transform M-band is applied on the 1D obtained signal. Then, the Rényi based information measure is computed on sub-bands coefficients in order to characterize the anisotropy which is strongly present in our application related to bone radiograph characterization. Finally, the Wilcoxon test is used on the Rényi entropies obtained for each subband and the K nearest neighborhoods classifier is used with the Rényi divergence as a distance. Applied on two different populations composed of osteoporotic (OP) patients and control (CT) subjects, a classification rate of 98% is achieved which provides a good discrimination between OP patients and CT subjects.

Index Terms— Texture, Dual Tree M-Band, Rényi Entropy, Rényi Divergence, Bone, Osteoporosis.

1. INTRODUCTION

Bone disease like osteoporosis is characterized by a severe decrease in bone mass and alteration of the microarchitecture of bone tissue. Osteoporosis is considered as a major public health issue [1] due to an increase frequency of fractures of the hip, spine, and wrist. 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 assessed clinically using the bone mass density (BMD). This technique is very suitable, but gives no information about the alteration of the microarchitecture of the bone tissue. The realization of a process detecting these alterations to predict the risk of osteoporotic fractures for a patient will complete and offer a better diagnosis [3]. This process has to be independent and complementary to BMD. Obviously, it has to be non invasive for the patient, not expensive, reproducible and efficient. The calcaneus (the bone of the heel) is a suitable site for the characterization of the bone microarchitecture. The calcaneus is subjected to pressure and compression produced by walking and gravity of the body (Fig.1). In the case of a normal subject, the compression and tensile trabeculae are uniformly distributed and cross each other. For an osteoporotic patient, the tensile trabeculae may disappear making the structure anisotropic. The modifications of the organization of the trabeculae and their thickness can help evaluating the damage of the bone. Several studies have attempted



(a) (b)

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

to evaluate osteoporosis using three-dimensional (3D) non-invasive measures to analyze the trabecular bone structure. Despite the accuracy of this type of measure, it is less suited in practice due to its complexity, price, and accessibility to the devices; furthermore, it cannot be used *in vivo*. 2D texture analysis offers a simple way to evaluate the bone structure on conventional radiographs [4] and many studies have shown that 2D texture analysis can be considered as an indirect evaluation of the 3D microarchitecture of the bone [5, 6]. This enables the extraction of information about the bone structure and helps in distinguishing healthy from pathological cases.

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According to several studies [4, 7] the 2D texture analysis of osteoporosis seems to be a promising way to evaluate and detect osteoporosis efficiently.

Several studies have attempted to evaluate osteoporosis and to characterize the anisotropy of textured images using statistical or fractal analysis [8, 9]. These methods gave interesting results but are still under investigation for an efficient characterization of bone texture organization. The exploitation of the direct information present on bone radiographs is not mandatory. Enhancement of the data using suitable preprocessing methods can be of interest and might give better results than the raw data. Preprocessing includes geometric transformation (projection or summation of the data along an oriented axis) and frequency transformation (wavelet analysis).

In this work, we propose a method which enables characterizing the anisotropy of an image using the entropy and the divergence of Rényi and the Dual Tree M-Band. The Rényi entropy has shown its effectiveness especially to quantify the anisotropy [10]. Our experiment consists of a 2-step algorithm. First, the Rényi divergence is used as a comparison criterion for the *k*-NN classifier. Then, the Wilcoxon test is used to assess the ability of the Rényi entropy to distinguish between OP and CT subjects.

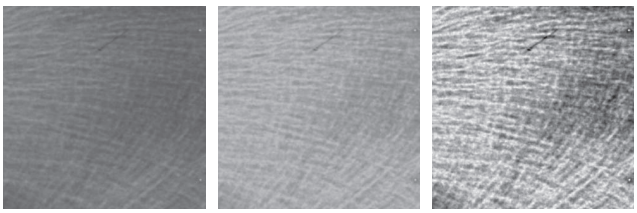
This paper is organized as follows. Section 2, describes the methods used to characterize trabecular bone data on radiographs. Section 3 presents the experimental results obtained on two different populations composed of osteoporotic patients and control subjects. Finally, some concluding remarks are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

2. METHODS

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 were enhanced. Then, several projections of the resulting images in different orientations were computed.

2.1. Preprocessing

To process the different data, first, we have used the Retinex algorithm introduced by Land *et al.* [11]. 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.* [12]. To keep and accentuate 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 2 shows an enhanced and quantized image of a bone X-ray image.



(a) (b) (c)

Fig. 2: (a) Original image of a calcaneus radiograph,(b) filtered image by the Retinex algorithm (c) and quantized image over 8 gray levels.

2.2. Projection

As can be seen on figure 2, trabeculae on textured bone X-ray images are organized with specific shapes and directions. To enhance shape information and improve the classification task of the different textures, we relied to image projection techniques. Projections are among the techniques that enables concentrating the information in a given orientation. Projections were computed by summing the gray level values of the image in each row, yielding a 1D signal. This operation can be repeated in different orientations by rotating the image throw different angles and performing the projection over rows.

2.3. 1D Dual Tree M-Band

The Dual Tree M-Band wavelet decomposition was initially proposed by Kingsbury [13] and taken over by Selesnick [14]. Dual Tree M-Band is based on the decomposition of the signal by two conventional filter banks operating in parallel. The first filter bank is called primal while the second is called dual. It is chosen so that the wavelets generated by banks are primal and dual pairs of Hilbert (Satisfying the condition of Hilbert). We have chosen the solution proposed by Chaux *et al.* [15], the Dual Tree M-Band Wavelet Transform. This kind of wavelet decomposition provides a local multi-scale analysis of the image through the projection. This way, we intend to better quantify the anisotropy of our textured images.

2.4. Rényi Entropy and properties

The Rényi entropy [16] is widely used for the description of anisotropic textures. The Rényi entropy results from the generalization of the Entropy of Shannon. It is an efficiently tool which has shown good performance [10]. The Rényi entropy of order α ($\alpha \geq 0, \alpha \neq 1$) is defined by:

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

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 $\alpha = 2$. The use of the Rényi divergence enables extracting more information between each subband. Let us define the Rényi Divergence. If P and Q are two populations belonging to the probability space (X, F), p and q the densities of the two populations. The Rényi divergence [16] is defined by:

$$Div(P,Q) = \frac{1}{1-\alpha} \log \int p^{\alpha} q^{1-\alpha} \qquad (2)$$

In this work, the Rényi divergence was used as a distance for our classifier and the Rényi entropy was used as a descriptor of each subband.

3. EXPERIMENTAL RESULTS

For this study, we considered a population composed of postmenopausal women suffering from osteoporotic vertebral crush fractures and control subjects. Among these 77 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 $2.7 \times 2.7\ cm^2$ was located in a region that contains only trabecular bone. The pixel size was $105\ \mu m$.To evaluate our method, we propose two experiments *EXP1* and *EXP2* which use the divergence and the entropy, respectively. In *EXP1*, the k nearest neighbors (k-NN) classifier was used for texture classification. k-NN has a single parameter k which needs to be tuned [17]. The cross validation hold out method with a ratio of 20% for the training set was used. For the comparison criterion, we used the Rényi divergence D_n as a distance between the obtained histograms of each subband resulting from the Dual Tree M-Bands decomposition. Further, the Receiver Operating Characteristics curves (ROC) [18] were used to measure the influence of k on the rate of the classification.

$$D_n(test_i, train_j) = \frac{1}{1-\alpha} \log \sum H^{\alpha}_{train_j} H^{1-\alpha}_{test_i} \qquad (3)$$

where $n = 1, \cdots, N$ and H_n represents the histogram of subband at level n. Once the divergences are calculated, we determine the distance matrix elements, $Dist$, between training items and test items.

$$Dist(test_i, Train_j) = \sum D_n(test_i, train_j) \qquad (4)$$

All the procedures were executed 100 times and the mean value was retained as a representative result. Figure 3 shows

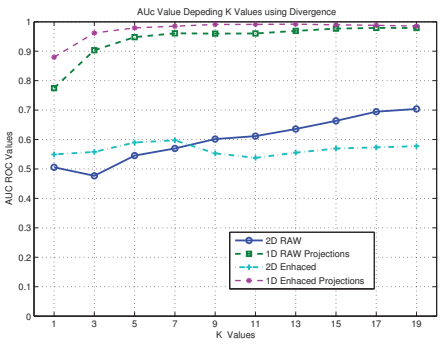


Fig. 3: ROC curves depending on k-NN values using the Rényi divergence

Angle	AUC Pretreated	AUC not Pretreated
0^o	0.987	0.951
45^o	0.511	0.512
90^o	0.787	0.921
135^o	0.670	0.657

Table 1: The values of the AUC depending on the angle of orientation

the evolution of the Area Under Curve (AUC) of the ROC curves while varying the parameter k of the k-NN classifier. Each graph corresponds to one of the proceeded data of this study: the original image (2D-R), the enhanced image (2D-E), the original image projected (1D-RP) and the enhanced image projected (1D-EP). For the projection, the angle of orientation is 0^o, *i.e* along the rows. As can be seen on figure 3, the enhancement improves the classification score. The best classification rate is obtained for the enhanced and projected image. $k = 7$ gives a good classification rate and seems to be a good compromise between efficiency and computation time. Due to the organization of the bone trabeculae, anisotropy plays a role in the stiffness of the bone. For this reason, the effect of the angle of analysis was also studied. Due to the discrete sampling grid and interpolation problems, only the angles multiple of 45^o were used. Table 1 presents the AUC values obtained for projections computed in different orientations. The best rate of classification was obtained for the 0^o orientation.

In *EXP2*, we studied the ability of the Rényi entropy to separate the two populations OP and CT over the scale levels. We used the Wilcoxon test [19], which evaluates the similarity between two populations. Table 2 reinforce the results found by the Rényi divergence. Meaning that the enhancement and the projection give the best rate of separation ($p < 0,005$) at 4 levels of scale. These results confirm that the Rényi entropy and the Rényi divergence are good candidates for the description of the bone tissue microarchitecture.

4. CONCLUSION

In this work, we have proposed an original approach based on Dual M-band transform and Rényi information measures for texture characterization with an application to bone X-

P-Value	Level 1	Level 2	Level 3	Level 4
2D-R	1.075e-07	1.031e-06	3.998e-03	1.328e-01
1D-RP	1.918e-05	6.672e-06	3.036e-05	1.458e-01
2D-E	6.073e-05	1.247e-04	1.385e-02	3.511e-01
1D-EP	5.695e-05	2.623e-05	1.587e-04	4.321e-04

Table 2: Obtained P-values with the threshold value $H = 0.005$ for the Dual Tree M-Band scale levels

ray images for the diagnosis of bone disease such as osteoporosis. Our technique combining different image preprocessing methods and the Rényi information measures shows that it is possible to achieve better classification rates to distinguish between two different populations composed of osteoporotic patients and control subjects. Depending on the orientation analyzed, results were different, proving that non-uniform changes due to osteoporosis induce variations in the degree of anisotropy. The statistical comparisons were done using the Wilcoxon test, the k-Nearest Neighbors classifier and the Receiver Operating Characteristics curves. This technique combined to Bone Mineral Density is a new opportunity for precise studies of bone disease such as osteoporosis. Further work will concern the investigation of the parametric model of oriented anisotropic textures.

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