Texture Characterization Using Local Binary Pattern and Wavelets. Application to Bone Radiographs

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Abstract— In this paper, we propose a method based on wavelet coefficients associated with 2D and 1D Local Binary Pattern (LBP) descriptors to classify X-ray bone images for bone disease diagnosis. The proposed approach uses two types of algorithms: the “À trous” algorithm that uses B-spline as a wavelet basis function and the “Mallat” algorithm with the Daubechie wavelet function. The wavelet decomposition is applied to the 2D image and to its projection. Then, the LBP descriptors are performed in both cases. Two approaches were adopted, the first one compares the LBP histograms and the second derives statistical measures from the histograms to form different feature vectors. Experiments were conducted on two populations of osteoporotic patients and control subjects. Results show that the 1D projected field of the 2D images achieves better results for the classification of the two populations.

Keywords— texture, classification, wavelet, anisotropy, bone, osteoporosis.

I. INTRODUCTION

Osteoporosis is considered as a public health issue [1]. The numbers of hip fractures worldwide are projected to increase almost 4-fold from 1990-2050 [2]-[3]. Prevention of fracture normally determines which populations are at risk for fracture. At the present time, osteoporosis has been defined as a disease characterized by low bone mass and microarchitectural alterations of bone tissue, leading to enhance bone fragility and consequent increase in fracture risk [4]. One of these two elements, bone mass is well evaluated in clinical practice by bone mineral density (BMD) determination, whereas the other one, microarchitectural alterations, is not [5]. The development of a useful microarchitecture indicator providing an appropriate risk factor of osteoprotic fractures would lead to a better diagnosis of osteoporosis [6]. This indicator should be independent from BMD and thus yield complementary information versus BMD to osteoporotic bone changes. It also must be reproducible, convenient, noninvasive, and inexpensive. For a long time, trabecular bone microarchitecture has been characterized by histomorphometry [7]-[8] but this method is invasive and cannot be applied to large populations. Our goal is to develop a tool that allows distinguishing between two populations including patients with osteoporotic fractures (OP) and control cases (CT).

The calcaneus (heel bone) is well suited to measure the anisotropy (Fig 1(a)). This bone is submitted to compression and tension forces produced by the walking and by the gravity. As a result, it is a very anisotropic texture as shown in Fig 1(b). The evolution of the orientations of the trabeculae enables quantifying the degree of deterioration of the bone. For a normal subject both types of trabeculae are uniformly distributed. For an osteoporotic subject the number of tensile trabeculae decreases gradually until a complete disappearance for a patient with severe osteoporosis. On the other hand, compression trabeculae become thinner and their number decreases much less quickly during the disease. As a result, a radiograph of an osteoporotic subject will be more anisotropic than the normal subject.

![Calcaneus radiograph and its region of interest (white square) (a). Region of interest measuring 256 x 256 pixels (2.7 x 2.7 cm²) used for processing and testing (b).](image)

Texture analysis applied to trabecular bone images offers the ability of exploiting the information present on conventional radiographs [9]-[10]. There exists a wide variety of image texture analysis techniques, the main approaches use: Gauss Markov Random Fields (GMRF) [11], Gabor filters [12], histogram of local characteristics, [13]-[14]. However, the performance of each approach depends on the application and the type of the texture. Nevertheless, The Local Binary Pattern (LBP) method [13] have shown nice performance for different applications including texture phenomena. It is interesting to use such kind of approach for bone texture classification, for its simplicity and high discriminative properties for textures. However, the bone texture of osteoporotic and control patients is not much distinctive and needs deep expert analysis with prior acknowledge to separate the two classes of patients.

The calcaneus texture is characterized by both the direction of the global and the local patterns Fig 1(b). The aim of the presented work is, to validate the approach so called 1D LBP proposed in [16] applied in the high-pass wavelet coefficients sub-space. The technique consists in four stages procedure. First, a high pass spatial frequency

![Calcaneus radiograph and its region of interest (white square) (a). Region of interest measuring 256 x 256 pixels (2.7 x 2.7 cm²) used for processing and testing (b).](image)
filter is applied to keep the essential information of the texture. The second step is the quantization of the gray level texture from 256 to 16 gray levels. The third step, the image is projected onto vertical (see Fig 6) direction, next a Discrete Wavelet Transform (DWT) is performed to the 1D projected signals. Finally, the local binary pattern method is applied on the wavelet coefficients for each DWT decomposition level. Compared to the original LBP, the K-nearest neighbors classifier yields better classification rate of the two populations composed of osteoporotic patients (OP) and control subjects (CT) with the proposed approach.

The paper is organized as follows. Section II presents the preprocessing performed to enhance the data. The Local Binary Pattern methods are presented in section III. Combination of the LBP methods and the wavelet approach for feature extraction is described in section IV. Results are discussed in section V and the conclusion is drawn in the last section.

II. FEATURE ENHANCEMENT

Trabeculae in bone are organized so as to supply a mechanical resistance adapted to various constraints. Trabeculae in the directions undergoing weak constraints are less numerous and less thick. The non uniform changes due to osteoporosis induce variations of the degree of anisotropy. A precise analysis of the mean periodogram performed on the lines of trabecular images presents two distinct frequency regimes as shown on Fig 2. These two regimes are separated by a frequency cut \( f_C \). The low frequencies \(|f| < f_C\) or, equivalently, the large scales correspond to the intertrabecular area. While the high frequencies \(|f| > f_C\) or, equivalently, the small scales correspond to the trabecular area.

To sum up, the architecture of bone is mainly described by the arrangement of trabeculae and thickness. The evolution of architecture in osteoporosis results in variations at scales that match our images at high frequencies. To analyze the phenomena in this band, it would be necessary to perform preprocessing of the trabecular bone images to support this range of analysis. For this purpose we choose to make a high-pass filtering of the images. This filter is sometimes called “flattening of the image". According to Fig. 2, the first 20 spatial frequencies of the spectrum are removed before performing the next processing.

![Fig. 2. A representative mean periodogram (Power Spectral Density or PSD) of the lines of an X-ray calcaneus image.](image)

To emphasize the significance of this frequency cut, we have filtered two images from an osteoporotic patient and a control one. A circular filter in the frequency domain is used for this purpose. The high frequency part of these images is presented on Fig 3 (c) and Fig 3 (d). The low frequency part corresponds to the area which is not concerned by osteoporosis and belongs to the intertrabecular spacing. While the high frequency part corresponds to the area concerned by osteoporosis namely the trabecular area.

![Fig. 3. Original image of the calcaneus of an osteoporotic patient (a), control case (b), high pass filtered images (c) and (d) and high pass filtered and quantized images for 16 gray levels (e) and (f).](image)

Further, in our case, 256 values of gray levels are not useful for proper characterization of the image. To enhance the trabecular bone patterns we reduce the number of gray levels. A reduction to 16 gray levels provides better and easier exploitable images more convenient for bone texture analysis. Fig 3(e) and Fig 3(f) show the effect of quantization and the filtering processes. We can notice also, from these figures, the high visual similarity between the control cases and osteoporotic patients which make the classification task more difficult.

III. LOCAL BINARY PATTERN

A. Classical LBP

The LBP and its variants is a powerful method for texture description [13]-[15]. The operator labels the pixels of an image by thresholding the 3×3 neighborhood of each pixel with the center value and considering the result as a binary number. Then the histogram of the transformed image is calculated and can be used as a texture descriptor. An illustration of the basic LBP operator is shown in Fig 4. The LBP may fail in many cases for anisotropy phenomena since it is more complex than the natural textures. In the x-ray images of the bone, this phenomenon is characterized by the global direction of the trabeculae. The 2D local patterns are less sensitive to such characteristics, because they encode only the frequency of local structures regardless their global orientations. In the next section we present a method that uses local patterns to capture more information about global directions.

![Fig. 4. LBP operator performed onto a 3×3 neighborhood.](image)

B. One dimensional LBP

The 1D projection of row or columns of an image provides a tool to describe better the global and local patterns. Fig 6(b) presents an example of a vertical projection. Our aim is to validate the method so called 1DLBP [16] for 1D signals in wavelet field. The concept of the One Dimensional Local Binary Pattern, consists in a binary code describing the local agitation of a segment in a 1D signal. It is calculated by thresholding the neighborhood values of the central element. All the neighbors will get the value 1 if they are greater or equal to the current element and 0 otherwise. Then, each element of
the resulting vector is multiplied by a weight according to its position. Finally, the current element is replaced by the sum of the resulting vector. This can be summarized as follows:

\[ 1D\text{LBP}_{M,R} = \sum_{i=0}^{M-1} s(t_i - t_i)2^i \quad s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (1) \]

where \( t_i \) and \( t_i \) are respectively the values of the central element and its 1D neighbors. The index \( i \) increases from the left to the right in the 1D sequence (see Fig 5). The 1DLBP descriptor is defined by the histogram of the 1D patterns and is given by:

\[ H_k = \sum_{n= \delta \times \frac{M}{R} \times k} \delta \left(1D\text{LBP}_{M,R}(s[n]), k \right) \quad (2) \]

where, \( H_k \) is the LBP descriptor of the 1D projected signal, \( k \) is the number of bins \( (k = 2^{k-1}) \), \( \delta \) the Kroniker operator, \( R \) the size of the 1DLBP mask and \( M \) the number of neighbors.

![Fig. 5. Performing the 1DLBP on the central element of a 1D mask with 8 neighborhoods.](image)

**IV. WAVELETS AND FEATURE EXTRACTION**

Wavelets are the multiresolution techniques intend to transform an image into a representation in which information regarding both the nature of the frequency components (high or low) and the location of occurrence of these frequencies in the image axe preserved. For multiresolution decomposition of images, it is often desirable to differentiate the local orientation of the image features. In this study, both the Mallat and À trous algorithm [17]-[19], were used as multiresolution tools for feature extraction.

**A. À trous algorithm**

The À trous algorithm was one of the first methods proposed to perform a discrete wavelet transform (DWT) on mono-dimensional signals [17]-[18]-[20]. In this algorithm, the wavelet expansion is not performed by sub-sampling the image. This implies that the various approximations of the image and the images of all wavelet coefficients have the same size as the original image. The mono-dimensional approximation of the signal at the resolution \( 2^j \) is calculated from the approximation of the signal at resolution \( 2^{j-1} \) using the following equation:

\[ f_{j+1}(t) = \frac{1}{4} f_{j}(t - 2^j) + \frac{1}{2} f_{j}(t) + \frac{1}{4} f_{j}(t + 2^j) \quad (3) \]

The difference between two successive approximations is described by the wavelet coefficients:

\[ C_{j+1}(t) = f_{j+1}(t) - f_{j}(t) \quad (4) \]

**B. Mallat algorithm**

In 1989, Mallat and Meyer introduced the concept of the multiresolution analysis applied to the image domain. The separable scale function was defined by:

\[ \varphi(x, y) = \varphi_{j,k}(x) \varphi_{j,k}(y) \quad (5) \]

where \( \varphi_{j,k}(x) \) and \( \varphi_{j,k}(y) \) are related respectively to \( x \) and \( y \) directions. The expression of the difference in existing information between two successive approximations of the same image is carried out using three directional wavelets, \( \psi^{xx}, \psi^{yy} \) and \( \psi^{xy} \). These wavelets allow the calculation of the difference of the information in the diagonal, horizontal and vertical directions. The high-pass band wavelet coefficients at resolution \( 2^j \) are given by:

\[ D_{2^j}^{xx} = \{f(x,y), \psi^{xx} (x - 2^j n, y - 2^j m)\}_{n,m} \quad (6) \]

In the 1D case, the calculation of the successive approximations is performed using digital filters. In the 2D case, the filters will be applied first to the rows then to the columns [19].

**C. Feature extraction**

In this section two approaches in wavelet coefficients sub-space were investigated in both 2D and 1D field. The first one, consist in combining the LBP technique and wavelets coefficients to extract a texture descriptor. The second approach, consists to compute 7 statistical texture features from the normalized LBP histograms in each DWT decomposition level. These measures are: the maximum value, the average gray level, the standard deviation, the Skewness, the Kurtosis, the mean/median absolute deviation and the entropy. The proposed method can be summarized as follows:

1) **Algorithm 1:**

**Step1:** Preprocess the original image.

**Step2:** Project the enhanced image in the horizontal or vertical direction.

**Step3:** Compute the 1D DWT on the projected signal to the third level of resolution.

**Step4:** Perform the 1D LBP descriptor on the wavelet coefficients for each of the 3 resolutions.

**Step5:** Concatenate the 1D LBP histograms obtained in step4

The same above steps were performed in the 2D case without projections, but using the 2D DWT decomposition and the 2D LBP in step 3 and step 4. Fig 6 depicts an example of the diagram of the algorithm 1 for the vertical projection.

2) **Algorithm 2:**

**Step1:** Preprocess the original image.

**Step2:** Project the enhanced image in the horizontal or the vertical direction.

**Step3:** Compute the 1D DWT on the projected signal to the third level of resolution.

**Step4:** Perform the 1D LBP descriptor on the wavelet coefficients for each of the 3 resolutions.

**Step5:** Compute the 7 statistical texture measures from the normalized LBP histograms obtained for each wavelet coefficients sub-space.

**Step6:** Compute the 7 statistical texture measures from the normalized LBP histograms obtained for the last wavelet approximations sub-space.

**Step7:** Concatenate the feature vectors obtained in step5 and 6.

Similarly the above algorithm can be applied in the 2D case using the 2D DWT and the 2D LBP in step 3 and step 4. In this case, the step 2 is removed since there is no projection.
V. EXPERIMENT RESULTS AND DISCUSSION

Experiments were conducted over clinical study data obtained with standardized protocol. The Calcaneus radiographs were obtained thanks to an X-ray clinical apparatus using a tungsten tube and an aluminum filter of 1-mm thickness. The tube voltage was fixed to 36 kV and the exposure condition was 18 mA, with an exposure time of 0.08 s. The source-calcaneus distance was settled at 1 m, and the calcaneus was placed in contact with the sensor. An image of a region of interest (256 x 256 pixels) from calcaneus radiography is extracted thanks to two anatomical marks (Fig 1(a)). This region was scanned with 256 gray levels to obtain a trabecular bone texture image as presented in Fig 1(b).

Fig. 6. Enhanced radiographic trabecular bone image from an osteoporotic patient (a), resulting 1D projected signal in the vertical direction (b), the wavelet coefficients from three resolution using the “À trous” algorithm (c), the corresponding 1D LBP features (d) and the resulting feature vector (e).

The proposed technique was applied on bone radiographs of a population composed of 80 women, provided by the medical stuff at the hospital of Orléans. Among these subjects, there were 39 patients with osteoporotic fractures (OP) (vertebral fracture) and 41 control cases (CT) without osteoporosis. Because age has an influence on bone density and on trabecular bone texture analysis, the fracture cases were age-matched with the control cases. The aim is to detect the patients with osteoporosis disease using the classification procedure. For that purpose, the k-nearest neighbors (k-NN) classifier with the Euclidean distance is used to validate the proposed approach. The number of k-NN is set to 11 neighbors, because all methods showed better performances for this value. The (k-NN) classifier is used with K-folds cross validation procedure, the dataset was partitioned into 10 subsets of equal size (8 elements per each set) selected randomly. Each subset was used in turn as the test set, the remaining subsets being the training set. For each sample we obtained a classification rate (% of images classified in the correct class) that consists in the ratio of the nearest neighbors with correct class to the total number of nearest neighbors.

Fig. 7. Algorithm 1 ROC curves for horizontal projection k-NN being equal to 11 obtained respectively by Mallat DWT in (a) and À trous DWT in (b), 1DLBP in green and for LBP in blue.

Figures 7 and 8 present the classification performance with Receiver Operating Characteristic (ROC) curves. Figures 7 (a) and (b) compares the 1D and 2D approaches with Algorithm 1, using Mallat and “À trous” DWT, the 1D signal is obtained from the horizontal projection. We can notice that the 1D approach shows best scores in both cases, but Mallat DWT gives better results in the 1D case. In contrast the “À trous” DWT is superior for the 2D approach. The same finding for Algorithm 2 and the 1D vertical projection in Fig. 8. The horizontal projection provides higher scores than the vertical projection. In order to explore further the performances, other measures estimated. It includes the AUC (Area Under Curve) of ROC curves, the sensitivity (SE), the specificity (SP), the F1-Score (F1-S) and the accuracy (Acc).

Table 1 summarizes the results of the performed tests for the horizontal projection. We can also observe that the 1D approach outperforms the 2D approach in all cases. Generally, for the 1D case the first algorithm with Mallat DWT provides the best classification score. Whereas, the “À trous” DWT works better with Algorithm 2, where it yields close scores to the first Algorithm with Mallat DWT.
The obtained results indicate that the proposed approach provides a tool that can help early diagnosis of osteoporosis and can be used to complete standard densitometry.

VI. CONCLUSION

This paper presents a method based on wavelet coefficients and the local binary pattern descriptors for X-ray bone image classification. First, to enhance the data and exhibit the trabecular bone pattern, a preprocessing is performed on the bone X-ray images. For the wavelet decomposition, two methods were used: the “À trous” and the “Mallat” algorithms. The LBP descriptors were applied to the original images and their resulting 1D vertical and horizontal projections. For the later, two approaches were adopted, the first one compares the LBP histograms and the second derives statistical measures from the histograms to form different feature vectors.

Using the k-NN classifier, the ROC curves as well as the features extracted from the histograms, this approach was used to distinguish between two different populations composed of osteoporotic patients and control subjects.

In term of AUC (Area Under Curve), the classification performance scores were highly improved using the 1D projections showing that the combination between the wavelet decomposition and the LBP descriptors is of great interest.

The obtained results indicate that the proposed approach provides a tool that can help early diagnosis of osteoporosis and can be used to complete standard densitometry.

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