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TEXTURE ANALYSIS OF RADIOGRAPHS IN THE ASSESSMENT OF OSTEOPOROSIS

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Abstract

Multi-channel filtering implemented using Discrete Wavelet Transform (DWT), is capable to mimics characteristics of the human visual system. In the assessment of osteoporosis, DWT was used to calculate features from trabecular pattern recorded on radiographs of proximal femur. The assessment of osteoporosis can be done by observing and analyzing the trabecular pattern in proximal femur. The feature extraction method used is energy computation. The energy then will be used for assessment or classification. The predetermined Singh Index of trabecular pattern are used to justify the classification result.

1 Introduction

With the better of life expectancy the risk of facing diseases causes by aging process in increasing. One of that disease is the loss of bone mass or osteoporosis. Earlier detection of osteoporosis can be done by using Bone Mineral Densitometry (BMD) technique using various mode such as ultrasound or Dual Energy X-ray Absorptiometry (DEXA). For the time being DEXA is considered as a gold standard for detection of osteoporosis.

The price of DEXA equipment is quite expensive. Currently only one DEXA equipment available in Indonesia. For less expensive osteoporosis detection most physician observed the change of trabecular pattern in proximal femur recorded in the radiograph as proximal femur has the largest trabecular pattern. Figure 1 shows the principal trabeculae in proximal femur which are considered as texture. There two major trabeculae, the principal compressive trabeculae and the principal tensile trabeculae [4].

On radiographs cancellous (trabecular) bone structure appears as a distinct pattern. The characteristic change of this distinctive pattern tell whether somebody has a healthy or osteoporotic bone. The use of trabecular pattern change for the diagnosis of osteoporosis was first proposed in the 1960s using radiographs of proximal femur. The diagnosis was known as Singh Index grading system but always been considered too variable for diagnosis or epidemiology [4], [5], [6], [7].

Currently the assessment of patient osteoporosis level is performed by direct observation of radiograph by physician. After analyzing the texture of trabecular pattern recorded on radiographs the physician then assess [2) Faculty of Industrial Technology] the level or degree of osteoporosis based on widely used Singh Index (SI). The aims of this research was to help the physician in diagnosis of osteoporosis by providing quantitative information about trabecular pattern recorded in radiographs of proximal femur.

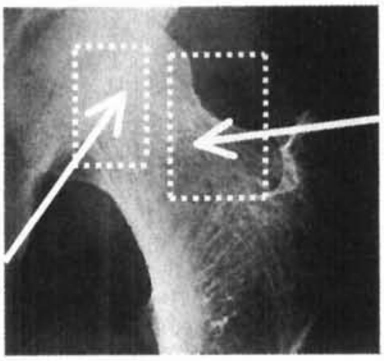

Figure 1. (a). Principal Compressive Trabeculae
(b). Principal Tensile Trabeculae

2 Texture Analysis

The texture analysis algorithm has wide range from random field model to multi-resolution filtering. Multi-resolution filtering or multi-channel is an effective consideration in the field of texture analysis. and could mimics characteristics of the human visual system (HVS) [3].

Research has shown that the HVS generates a multi-resolutional decomposition and the discrete wavelet transform (DWT) can be implemented as a multi-channel filter [3]. Multi-resolution filtering technique based on DWT will be used in texture analysis of trabecular pattern in proximal femur. The application of DWT to calculate features from textured images is motivated by capability of DWT to simultaneously minimize the two dimensional uncertainty in space and frequency [2].

DWT was applied to the classification of osteoporosis based on the change of trabecular pattern. The classification was based on features extracted by DWT in the form of energy. The result of classification then compared with predetermined Singh Index (SI).

3 Discrete Wavelet Transform

Continuous wavelet transform for 1-D signal, $f(x)$, defined as follows [2]

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$$(W_a f)(b) = \int f(x)\psi^*_{a,b}(x)dx \quad (1)$$

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \quad (2)$$

where wavelet $\chi_{a,b}$ computed from mother wavelet by translation and dilation. The 2-D form can be obtained using the product of 1-D filter.

Wavelet decomposition at J level can be written as

$$\begin{aligned} f_0(x) &= \sum_k c_{0,k}\phi_{0,k}(x) \\ &= \sum_k (c_{J+1,k}\phi_{J+1,k}(x) + \sum_{j=0}^{J} d_{j+1,k}\psi_{j+1,k}(x)) \end{aligned} \quad (3)$$

where coefficient $c_{0,k}$ are given and coefficient $c_{j+1,n}$ and $d_{j+1,n}$ at scale $j+1$ are related to coefficient $c_{j,k}$ at scale j through

$$c_{j+1,n} = \sum_k c_{j,k} h(k-2n) \quad (4)$$

$$d_{j+1,n} = \sum_k d_{j,k} g(k-2n) \quad (5)$$

where $0 \le j \le J$.

Mother wavelet constructed by scale function $\phi(t)$ and wavelet $\psi(t)$ which satisfies the two-scale relation as follows [1], [2]

$$\phi(x) = \sqrt{2}\sum_k h(k)\phi(2x-k) \quad (6)$$

$$\psi(x) = \sqrt{2}\sum_k g(k)\phi(2x-k) \quad (7)$$

where

$$g(k) = (-1)^k h(1-k) \quad (8)$$

Coefficient $h(k)$ should have orthonormal property and can be obtained from mother wavelet function such as Daubechies, Biorthogonal, Haar or Battle-Lémarie. Coefficient $h(k)$ is low pass filter and coefficient $g(k)$ is band pass filter.

To analyze discrete signal such as digital image, the discrete wavelet transform (DWT) should be used. In practice, DWT is computed by applying separated filter bank to signal $f(x)$ or image $I(x)$.

$$L_n(b_i, b_j) = [H_x * [H_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \quad (9)$$

$$D_{n1}(b_i, b_j) = [H_x * [G_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \quad (10)$$

$$D_{n2}(b_i, b_j) = [G_x * [H_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \quad (11)$$

$$D_{n3}(b_i, b_j) = [G_x * [G_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \quad (12)$$

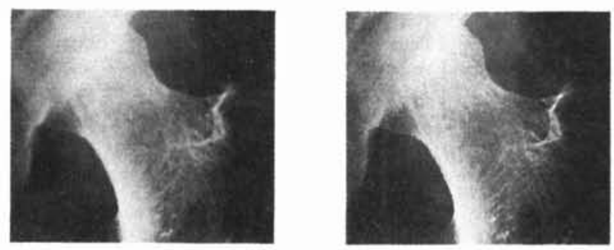
* is convolution operator, $\downarrow_{2,1}$ ($\downarrow_{1,2}$) is sub sampling along row(column) and $L_0 = I(x)$ is original image. H and G is low pass and band pass filter respectively. L_n is the result of low pass filtering and thus referred as low resolution image at scale n. D_{ni} is obtained from band pass filtering at certain direction and thus containing detail direction information at scale n and called as detail image. Original image I is represented by a set of sub image at different scale: $\{L_d, D_{ni}\}_{i=1,2,3;\ n=1..d}$ which is the multiscale representation with depth d of image I. For this research, the mother wavelet function used is Haar wavelet.

4 Radiographs Pre-Processing

Before analyzed by DWT, the radiographs were pre-processed to achieve better image quality. The radiographs were pre-processed with series of filter like high-pass, wiener and median filters. The block diagram of pre-processing steps is

Figure 2. Block diagram of pre-processing

Figure 3 shows the example of original radiograph and the result of pre-processing.



(a) (b)

Figure 3. (a) Original radiograph, (b) Result of pre-processing

5 Feature Extraction

Extraction of wavelet features was performed using energy computation as follows

$$e(x) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|x(m,n)|^2 \quad (13)$$

for wavelet images $x(m,n)$ with $1 \le m \le M$ and $1 \le n \le N$.

Wavelet features were calculated on certain region of interest (ROI) of proximal femur known as Ward's triangle. The Ward's triangle is region that most sensitive to bone mass lost [7]. Figure 4 shows the ROI used in this paper.

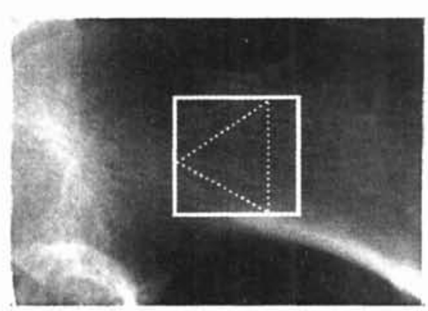


Figure 4. Region of Interest (ROI).

Feature images produced by applying ROI images to DWT at first scale are shown in Figure 5.

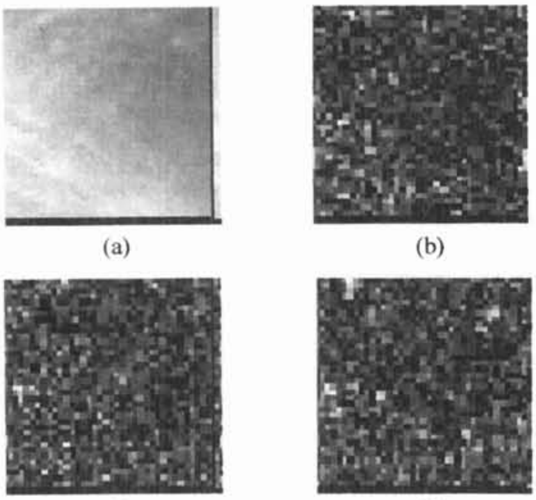


Figure 5. Wavelet feature images at first scale.
(a). Approximation coef., (b). Horizontal detail coef.
(c) Vertical detail coef., (d). Diagonal detail coef.

6 Application to Texture Analysis of Radiographs

In this paper we used four different trabecular pattern recorded in 55 patient radiographs. The four trabecular pattern are shown in Figure 6.

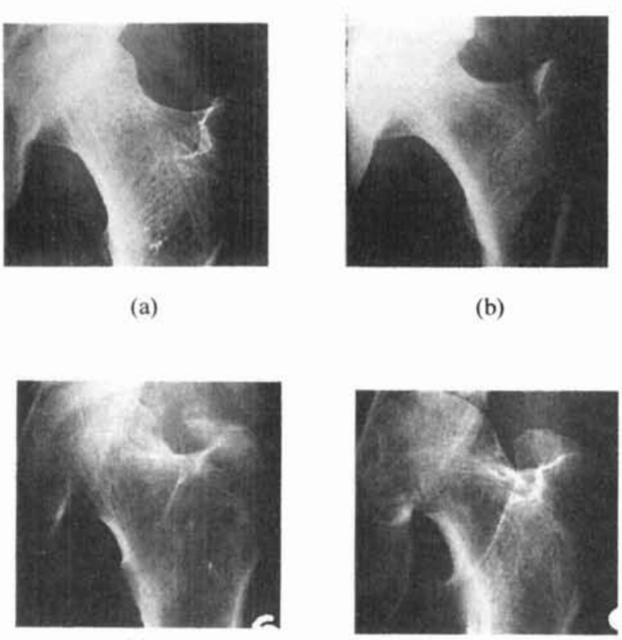


Figure 6. Five different trabecular pattern.
(a). Grade 6, (b). Grade 5, (c). Grade 4, (d). Grade 3.

These trabecular pattern has been examined by physicians and classified as grade 6 to grade 3 according to Singh Index. The higher the grade the better the bone quality. The feature extracted from wavelet features by energy computation then compared to predetermined Singh Index to investigate the capability of wavelet features to assess the degree or level osteoporosis.

The result of features extraction or energy computation by applying DWT in four scales or levels decomposition using Haar wavelet for one radiograph sample is shown in Table 1.

Table 1. DWT features extraction (energy) in four scales using Haar wavelet

	'A'	'H'	'V'	'D'
Level 1	0.50	0.01	0.01	0.00
Level 2	0.51	0.02	0.01	0.01
Level 3	0.51	0.05	0.04	0.12
Level 4	0.54	0.09	0.08	0.02

From Table 1 it is clear that significant energies were obtained from level 2 and 3 decomposition for approximation coefficient. Therefore for the rest of the radiographs samples, features extraction will be computed for approximation coefficient at level 2 and 3 decomposition. The result of energy computation for 55 radiographs samples is shown in Figure 7.

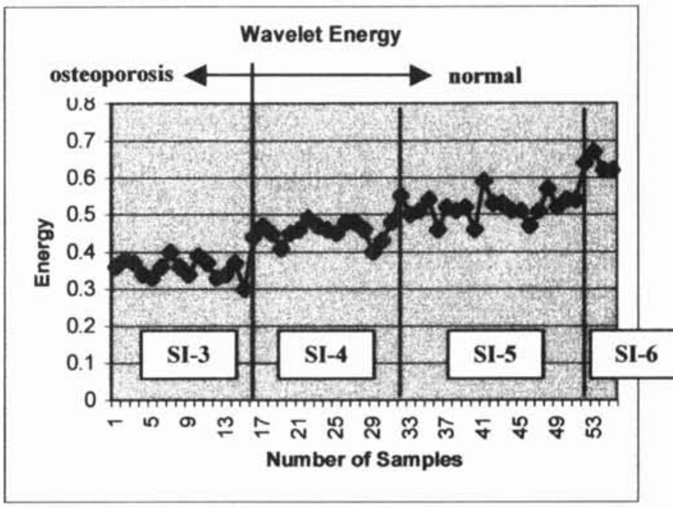


Figure 7. Extracted features (energy) of 55 radiographs

The energy computed from trabecular pattern of grade 6 samples appear to be higher than the energy from samples of the grades 5, 4, and 3 respectively. The healthiest bones, which are the grade 6 samples, have the highest energy. The osteoporotic bones, which are the grade 3 samples, have the lowest energy.

7 Conclusion

The discrete wavelet transform has successfully applied to texture analysis of the trabecular pattern recorded in the radiograph of proximal femur. The extracted features from trabecular pattern in the form of energy were able to give information about the quality of the bones in the assessment of osteoporosis.

References

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