

A DIGITAL IMAGE PROCESSING APPROACH TO DIAGNOSIS OF OSTEOPOROSIS

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Abstract

Digital image processing texture analysis methods are implemented to detect and quantitate trabecular pattern changes for computer-assisted diagnosis of bone loss diseases. Techniques are described for extracting certain textural features, namely, run length statistics, fractal dimension and relative extrema density from standard film radiographs of trabecular bone. Results of a study are given which suggest that these features are able to quantitate changes that occur in a clinical disuse osteoporosis model.

INTRODUCTION

Osteoporosis is a bone disease that afflicts millions of people. Affecting mainly the elderly, and especially women, the disease results in a loss of bone with a concomitant reduction in the structural integrity of the skeleton. Consequently, people in advanced stages of the disease are prone to fractures, especially of the hip, the forearm and the vertebrae, and subsequently, many develop serious complications, including death. Therefore, it is of fundamental importance to identify those people in early stages of the disease so that early treatment, albeit, much of it experimental, can be given.

Currently, there is no clinical diagnostic technique which can consistently identify those people at high risk for fracture. The best approaches to osteoporosis diagnosis rely on quantitative measurements of bone density, e.g., dual photon absorptiometry and quantitative CT scanning. Such techniques have two major disadvantages. First, they are relatively expensive to implement since they rely on sophisticated equipment for measurement. Thus any large scale diagnostic screening program would be prohibitively expensive. Second, and more important, such density-based diagnostic procedures as mentioned above have been shown to be poor indicators of those patients in greatest fracture risk. This is, there are significant numbers of people with relatively high values for bone density yet who fracture their bones. Conversely, many of those with low values for bone density never experience a fracture. Thus, as is now reasonably well established, the strength of the cytoskeleton is determined not only by how much bone there is,

but also by how that bone is spatially (i.e., structurally) distributed.

In this study we attempt to develop a technique by which bone loss diseases can be diagnosed in an accurate yet relatively simple manner. Specifically, we have applied digital image processing techniques to bone radiographs for computer-assisted quantitative diagnosis of osteoporosis. Our work is based on the principle, as put forward by one of the authors¹, that early indications of osteoporosis are visible through changes in the trabecular patterns of bone viewed on standard radiographs. Since bone loss in osteoporosis is a surface phenomenon, and since cancellous bone is composed of both longitudinal (coarse) trabeculae and transverse (fine) trabeculae, then the first noticeable changes in bone radiographs are of the thinning and subsequent disappearance of the fine or cross-bracing trabeculae. This first stage of the disease is characterized by an apparent coarsening or roughening of the trabecular portion of the bone radiograph, and has been likened to an unveiling of the heretofore partially masked longitudinal or compressive trabeculae.

The above characterization of radiologic changes in osteoporosis led us to investigate the application of texture based pattern recognition methods for quantitative measurement and diagnosis of the disease process. Texture analysis has been applied before to pattern recognition problems, both for medical and non-medical purposes. For example, textural-based techniques are a well-known tool for detecting locations of specific geographical formations in satellite-based remote sensing². In medicine, texture analysis has been applied to the detection of various types of lung disease³; however, this is the first such application to diagnosis of bone loss disorders. Moreover, as discussed above, there is an underlying physical basis for applying textural-based methods to osteoporosis characterization, in contrast to other statistically motivated applications.

Methodology

A feasibility study was performed in order to assess the applicability of texture analysis to radiographs of trabecular bone. For this purpose, a disuse osteoporosis model was employed. In particular, we analyzed changes in os calcis trabecular patterns of 5 patients who have been non-weight bearing for several weeks or months because of an ankle fracture. The x-ray image at the time of fracture was considered to be the baseline for each patient and subsequent images were compared for trabecular pattern changes over a period of 1 month to 5 years post-fracture. Analysis of the images was restricted to a standardized 2 cm² area encompassing most of the major compressive trabeculae of the calcaneus. The film radiographs were digitized from a light box using a video camera interfaced to an IBM PC/AT computer using an A/D interface board (Imaging Technology, Woburn, MA) and image processing software (Werner Frei Associates, Santa Monica, CA). The 512x512x8 bit digital images were stored on disk for off-line processing and analysis. Initially, all images were histogram equalized to compensate for variations in grey level distribution. Similar results to those presented below were obtained through mean and contrast normalization.

Several algorithms for texture analysis were implemented on computer and applied to the digitized radiographs. We explored the use of run length statistics, fractal dimension, and relative extrema density as potential discriminators of bone pathology. In particular, the features used for quantitating trabecular bone pattern changes are:

(1) $r = L/S$, a run length statistic⁴ defined as the ratio of long emphasis (L) to short run emphasis (S), where

$$L = \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} j^2 p(i,j) \right\} / \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j) \quad (1)$$

$$S = \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)/j^2 \right\} / \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j) \quad (2)$$

Here, N_g and N_r are the number of grey levels and run lengths, respectively, and $p(i,j)$ is the number of times there is a run of length j of grey tone i . These calculations are performed for angular directions of 0, 45, 90 and 135 degrees, and the results averaged to give the final statistic r ;

2) f , which characterizes the variation in the measured surface area of the digital image as a function of an elemental measuring surface. This description of texture is based on the fractal

geometry of Mandelbrot⁵. The digital image is assimilated to a 3-D surface, the grey level being the third dimension, and $A(e)$ is the surface area as a function of the surface measuring element, given by:

$$A(e) = [V(e) - V(e-1)]/2 \quad (3)$$

where

$$V(e) = \sum_{i,j} \{ U_e(i,j) - B_e(i,j) \} \quad (4)$$

U_e and B_e are the upper and lower measuring 'blankets' or set of points with distance to the surface of no more than e units from the upper (respectively, lower) side, and are given by

$$U_e(i,j) = \max \{ U_e(i,j) + 1, \max_{|(m,n)-(i,j)| < 1} (U_{e-1}(m,n)) \} \quad (5)$$

$$B_e(i,j) = \min \{ B_e(i,j) + 1, \min_{|(m,n)-(i,j)| < 1} (B_{e-1}(m,n)) \} \quad (6)$$

for $e=1,2,3,\dots$, and B_0 and U_0 are initialized to $g(i,j)$, the image grey levels⁶. The feature f is taken to be the slope of the best fit (least-squares) straight line through the three points $(1,A(1))$, $(2,A(2))$, $(3,A(3))$;

(3) N , the number of relative extrema of pixel values along a line in the image. This statistic is based on the work by Mitchell, et al.⁷ and attempts to characterize texture in an image by using the relative frequency of local extrema in grey level as the principal measure. The algorithm is described as follows⁷. Let g_k be the grey level of the k th point along the scan line and let y_k be the "smoothed" value. Let δ be the value of a preassigned threshold parameter (chosen here empirically). Start with $y_1 = g_1$ and proceed according to the algorithm shown below:

<u>IF</u>	<u>THEN</u>
$y_k < g_{k+1} - \delta/2$	$y_{k+1} = g_{k+1} - \delta/2$
$g_{k+1} - \delta/2 < y_k < g_{k+1} + \delta/2$	$y_{k+1} = y_k \quad (7)$
$g_{k+1} + \delta/2 < y_k$	$y_{k+1} = g_{k+1} + \delta/2$

The number of relative maxima in the smooth curve y_k are counted and used as a feature of the radiographic image of trabecular bone.

RESULTS

Results that we have obtained indicate that changes do occur in bone during osteoporosis which can be detected and quantified through digital image processing of the film radiograph using the above three features. These changes as reflected through the feature space appear to be related to a general coarsening of the radiograph during the initial stage of disuse osteoporosis, and this is detected through variations in the texture features. For example, the run length statistic r was generally observed to increase shortly after the beginning of the non-weight bearing period. This increase agrees with visual inspection of the image since coarse textures have many pixels in a constant grey tone run and fine textures as having few pixels in a constant grey tone run. This is illustrated in fig.1, where the run length statistic r averaged for five patients is plotted. Note that each patient's ' r ' value was normalized by the value for ' r ' at the time of fracture.

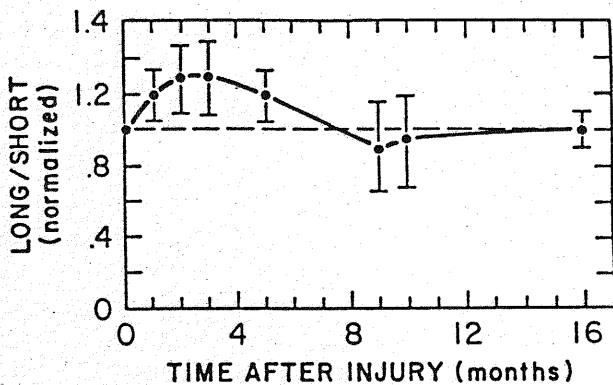


FIGURE 1: RUN LENGTH STATISTIC ' r '

Two digital radiographic images of trabecular bone appear in fig. 2, one at the time of fracture (fig. 2a) and the other 5 months post-fracture (fig.2b). The associated relative extrema curves are presented in fig. 3, and indicate that disuse osteoporosis leads to a reduction in the number of relative extrema (Table II). This particular feature should be especially relevant to the diagnosis of bone loss diseases since it is a statistical representation of the trabecular bone spacing and density. These radiographic analyses may also have significance with respect to their ability to predict the overall biomechanical competence of trabecular bone⁹.



(a) at fracture

FIGURE 2: RADIOGRAPHS OF HUMAN OS CALCIS (HEEL)



(b) 5 months post-fracture

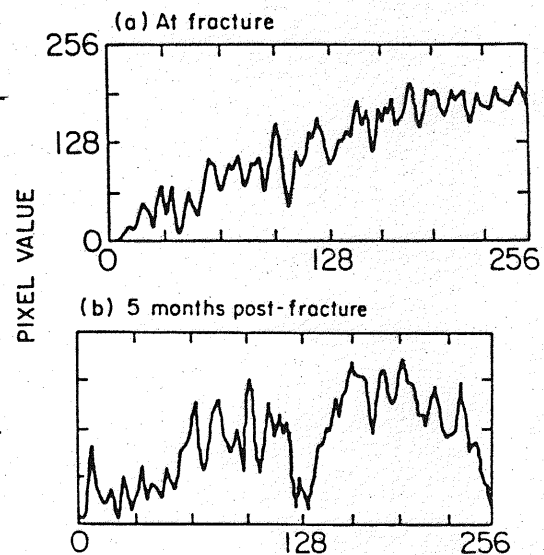


FIGURE 3: GREY LEVEL CURVES ASSOCIATED WITH FIG. 2

Conclusion

This paper reports on an initial investigation of the use of digital image processing and texture analysis techniques to characterize bone loss diseases from standard x-ray images. Our results indicate the clinically observed bone loss may be able to be detected and quantified through changes in features derived from radiographic images of trabecular bone. Further work must be done in order to examine the sensitivity of these texture features to variations in the radiological procedure. We are currently incorporating an aluminum wedge into the x-ray image in order to compensate for exposure and film development artifacts and to investigate the sensitivity of the pattern recognition procedures employed to variations in radiographic procedure. The wedge also allows the incorporation of densitometric measurements into the feature space. We are also currently investigating the application of textural features to CT scans of human vertebrae. The results of these studies should lead to a better understanding of how trabecular architecture is affected by various disease processes and consequently, to our ability to more accurately diagnose bone loss diseases through texture analysis and other pattern recognition techniques.

TABLE II: RELATIVE EXTREMA DATA

PATIENT	MONTHS AFTER FRACTURE							
	0	1	2	3	5	9	16	60
AM	27		23	21	23	21		
CF	31	22			22		27	
AS	23	21			19			18

Similar results were obtained using the fractal dimension parameter f (Table I). Note that as with the run length statistic, an increase in f value is generally associated with a coarsening of the image. Also note that there appears to be about the same dispersion around the mean value for both the run length and fractal parameters. A more detailed discussion of fractals for texture analysis in bone loss diseases is discussed by Ohley, et al.⁸

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TABLE I

FRACTAL DIMENSION

IMAGE	MEAN f	RANGE
injury	2.51	2.44-2.53
1-5mo	2.55	2.43-2.58
9mo-2yr	2.49	2.47-2.52

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