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THE MEASUREMENT OF BONE QUALITY USING GRAY LEVEL CO-OCCURRENCE MATRIX TEXTURAL FEATURES

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Abstract

In this paper, statistical methods for the estimation of bone quality to predict the risk of fracture are reported. Bone mineral density and bone architecture properties are the main contributors of bone quality. Dual-energy X-ray Absorptiometry (DXA) is the traditional clinical measurement technique for bone mineral density, but does not include architectural information to enhance the prediction of bone fragility. Other modalities are not practical due to cost and access considerations. This study investigates statistical parameters based on the Gray Level Co-occurrence Matrix (GLCM) extracted from two-dimensional projection images and explores links with architectural properties and bone mechanics. Data analysis was conducted on Micro-CT images of 13 trabecular bones (with an in-plane spatial resolution of about 50 μ m). Ground truth data for bone volume fraction (BV/TV), bone strength and modulus were available based on complex 3D analysis and mechanical tests. Correlation between the statistical parameters and biomechanical test results was studied using regression analysis. The results showed Cluster-Shade was strongly correlated with the microarchitecture of the trabecular bone and related to mechanical properties. Once the principle thesis of utilizing second-order statistics is established, it can be extended to other modalities, providing cost and convenience advantages for patients and doctors.

Keywords

medical imaging; bone; texture; DXA; GLCM; osteoporosis

1. Introduction

Osteoporosis is a skeletal disease in which loss of bone mass and deterioration of bone microarchitecture cause a reduction in bone stiffness and strength, thus resulting in an increased risk of fragility fractures. Spine fractures are the most common type of osteoporotic fractures and these are a major concern for health care of elderly population. Therefore, early diagnosis of patients with high risk of osteoporotic fractures is essential.

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Conflict of Interests

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Dual-energy X-ray Absorptiometry (DXA) is one of the most popular ways of estimating bone strength and fracture risk in bone loss diseases such as osteoporosis. This is because it can test bone mass loss which would be the result of osteoporotic changes. DXA's insensitivity to architectural changes masks an important factor contributing to bone strength which cannot be ignored. The new methods of 3D image analysis such as stereology principles, which provide architectural information are so costly that they are impractical as a clinical solution. Researchers are developing new practical techniques which are based on mathematical analysis of the two dimensional plain-projection image obtained from the three-dimensional tissue images of the DXA.

Trabecular structure is important in osteoporosis clinical applications. Turner ¹ has proved that incorporating both density and architecture can improve the bone strength predictability to 90%. Two-dimensional projection of the bone images can be utilized to measure "texture". Luo and Kinney ² show that texture information related to trabecular structure is conserved during the transformation from 3D to 2D images using software analysis. Many texture analysis algorithms have been applied to bone images to estimate their architecture quantitatively. Fractal analysis of X-ray textures has been used for identification of osteoporotic patients ^{3,4}. Chappard ⁵ uses run-length distribution texture analysis methods on X-ray radiographs to prove that it is a reliable descriptor of bone loss in a rat bone model. Recent studies also indicate that Markov Random Field based models such as semivariograms are capable of assessing bone characteristic properties ⁶⁻⁸. The Trabecular Bone Score (TBS) has gained the attention of researchers in the assessment of fracture risk ^{9,10}. TBS is a new parameter determined from the grayscale analysis of DXA images ¹¹. The value of TBS is calculated as the slope at the origin of the log-log representation of the experimental variogram of DXA images ¹²⁻¹⁴. In ex vivo studies, TBS has been found to correlate with microarchitecture parameters of trabecular bone, such as bone volume fraction, mean bone thickness, degree of anisotropy and structure model index (SMI) ^{11,14,15}. TBS has also been used in numerous clinical studies ^{9,10,12,13,16-19}.

GLCM has become an increasingly popular texture analysis method since the original studies by Haralick ^{20,21}. Many researchers have applied it to the geosciences and remote sensing fields such as SAR sea ice ^{22,23}, desert ²⁴, cloud ^{25,26} and soil ²⁷. The authors believe that this method has a lot of potential for exploration in medical imaging. The goal in this project is to use GLCM based features to detect its parameters and its relationship with quality of bone.

Texture information could be extracted by statistical analysis of these two dimensional images. "Texture" as it is used in this context refers to the visual effect produced by the spatial distribution of pixel value variation over relatively small areas. Textural information can be either coarse or smooth. The coarseness index is related to the spatial repetition period of the local structure. Textural information translated into the bone's microstructure can be seen in the bone's volume fraction. It can also be perceived in other properties of the image.

The computation of gray level co-occurrence matrix (GLCM) as a second-order texture measure is one of the popular methods in texture analysis. Several statistical parameters can

be extracted from the GLCM, to quantify the spatial relationship between pixels within the area under investigation. In order to qualify characteristics of textures, different GLCM features including energy, contrast, entropy, autocorrelation, correlation, inverse difference moment, Cluster Shade have been studied^{20, 21}. The intent is to identify a measure of Bone Strength so that fracture risk can be assessed numerically. This study aims to investigate the relationship between 2D projection images and bone properties. Such relationship may have clinical significance because 2D projection images are available from clinical densitometers.

2. Materials and Methods

Thirteen cylindrical specimens of cancellous bone from six males of different age ranges were used in this experiment. Three crucial parameters were obtained from the bone specimens: elastic modulus, strength; and bone volume fraction (BV/TV). The Micro-CT image data and mechanical test data were obtained from previous studies^{6, 8}.

2D to 3D Image Transformation

Two-dimensional projection images of bone images were generated by averaging the gray values of the slice images from the three-dimensional Micro-CT data²⁸ as shown in Figure 1.

Region-of-Interest

The region-of-interest (ROI) for statistical measurements from the bone images is limited to the trabecular part of the bone, since the other parts of the image will skew the measures computed. Of the many methods to isolate the region of interest, thresholding was chosen for this purpose²⁹. From a grayscale image, a threshold can be computed and used to create a binary image, which then acts as a template for the ROI. There may be some spurious areas still existing inside the interest region. In order to delete these blobs, many morphological methods can be applied, such as “dilation and erosion”³⁰, “the hit-or-miss transformation”, “opening and closing”³¹. The MATLAB function described as “*imfill*” was utilized for this purpose. This function fills holes in the binary image.

Histogram Equalization and Quantization

It has been proved that histogram equalization will provide better details of bone structure in X-ray images²⁸. This method uses the image's histogram to adjust its contrast³². Its function is similar to that of a histogram stretch but provides more consistent results across a wider range of images³³. If the probability of gray level r_i in an image is defined by $p(r_i) = n_i / n$; ($i=1, 2, \dots, L-1$), where L is the total number of possible gray levels, n_i is the total number of pixels, n_i is the number of pixels with gray level r_i . The cumulative distribution function (CDF) can be expressed as

$$c_i = C(r_i) = \sum_{k=0}^i p(r_k) = \sum_{k=0}^i \frac{n_k}{n}; (i=1, 2, \dots, L-1) \quad (1)$$

The inverse transformation from c to r can be used as below:

$$r_i = T^{-1}(c_i) \quad (2)$$

It should be noted that the method is applied only to the ROI from the previous step.

The number of gray levels is important as GLCM size depends on how many gray levels are present in the image. There is a tradeoff between the number of gray levels required for accurate description of textures and computational complexity. There are three major quantization schemes: (1) uniform quantization (2) Gaussian quantization and (3) equal probability quantization^{34, 35}. It was noted based on tests conducted with varying numbers of gray levels G used for computing the GLCMs, that >8 did not increase the discriminatory capability or the relevance of the results³⁶. Uniform quantization was utilized to reduce the number of gray levels in the bone images accordingly.

GLCM Computation

The Gray Level Co-occurrence Matrix (GLCM) is a primitive measure of texture³⁷. It represents the second order statistics in an image, and quantitatively measures the frequency of different combinations of pixel brightness values (gray levels) occurring in an image. The definition is as follows, suppose we have an image I to be analyzed in which: $L_x = \{1, 2, \dots, N_x\}$ is the number of columns, $L_y = \{1, 2, \dots, N_y\}$ is the number of rows, $G = \{0, 1, 2, \dots, N_{g-1}\}$ is the set of N_g quantized gray levels.

A GLCM is a square matrix for which the number of rows is equal to the number of the columns, and also equal to the number of gray levels. Each element in this new matrix is referred to as a “relative frequency” $g(i, j)$ between 2 pixels with gray levels i and j respectively. An additional condition is that the two pixels to be located at the ends of a predefined vector of length d and angle θ (Polar representation) or length d_1 and d_2 (Cartesian representation). One GLCM can be computed for each new vector $t = (d, \theta)$ and can be named G_t with each element $G_t(i, j)$ being the frequency of occurrence of the pixel value pair (i, j) .

Eight gray levels were used in this experiment with the uniform quantization scheme to extract features from the 2D projection image. A displacement value d was set to 1, 2, 3, and 4 for every test image. The tested orientations were 0, 45, 90 and 135 degrees. Seven different GLCM features commonly found in the literature were obtained from the experiment, namely; energy, contrast, autocorrelation, correlation, entropy, homogeneity, and cluster-shade. Hence for every tested image, 112 different data values corresponding to different orientations and displacement and features would be expected.

The GLCM feature Cluster-Shade parameter is defined below:

$$S = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i+j-\mu_x-\mu_y)^3 \cdot g(i, j) \quad (3)$$

where the means are given by the equation.

$$\mu_x = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} i \cdot g(i, j)$$

$$\mu_y = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} j \cdot g(i, j)$$

The Cluster Shade “*S*” emphasizes locally shadowed areas, and measures the symmetry of the matrix³⁸. It significantly relies on the GLCM sum of row and column moments. It can be positive or negative, determined by which side of the mean was favored. In other words, when the absolute value of Cluster Shade is high, the GLCM lacks symmetry.

Statistical Analysis

The textural feature data from the 2D projection image was correlated with the data obtained from the mechanical tests. Linear regression methods were used to model the relationship between the mechanical test data (*y*) from 3D technique and experimental data (*x*) from the 2D projection image, described further in the next section.

3. Results and Discussion

For each bone, the texture features extracted from the GLCM (*x*), were analyzed for a statistical fit with the mechanical test data (*y*). The mechanical testing indicated various levels of strength in trabecular bones: weak bone, medium bone, and strong bone. Orientation is very important for many of the GLCM parameters. The “Coefficient of Determination *R*²” values were checked one by one for each parameter and each orientation. A sample analysis of results is shown below.

Table 1 and Figure 4 show us the correlation of energy and homogeneity to Elastic Modulus when orientation is 0°, and displacement is 1. It can be concluded that these measures are only partially related with Elastic Modulus.

Table 2 shows similar results for other textural features derived from the GLCM matrices. It can be seen that the coefficient of determination is not very high for the energy, entropy, contrast, homogeneity, correlation and autocorrelation GLCM features.

Figure 5 shows *R*² value in linear regression model when displacement is one and the four directional results are averaged for various GLCM features. It can be seen that the 'Cluster-Shade' GLCM feature correlates well in multiple orientations and distances when applied to real bone parameters including the Elastic Modulus, strength, bone volume fraction (BV/TV), with especially strong fits with the BV/TV value. Further analysis of the results for each bone parameter with Cluster Shade is presented below.

Table 3, shows the coefficients of determination obtained when the bone volume fraction parameter BV/TV was fit with GLCM feature Cluster Shade for various displacements and orientations. The highest value equals 0.879 (*d*=4, orientation = 0 degrees).

Figure 6 shows the R^2 value for Cluster Shade and BV/TV when displacement is 4 and orientation is 0° .

Table 4 shows the computed Cluster Shade GLCM feature values in further detail for each bone sample (displacement = 2) and the coefficients of determination for bone parameter bone volume fraction (BV/TV) for different orientations.

The data analysis procedure was followed for each bone parameter originally measured from the cadaver bones. Table 5 and 6 show the regression analysis fits for bone parameters Elastic Modulus and Bone Strength. From Table 4, it can be observed that the orientation also plays a very important role. The correlation is maximum between the Elastic Modulus and Cluster Shade, especially when the displacement is set to 2, 3, 4 at 0 degrees. The values indicate that a higher Cluster Shade value correlates to a stronger bone with higher mechanical elasticity.

Cluster Shade relies on the directional means of the GLCM. In our experiments eight quantization levels were utilized and the directional means of the two dimensional projection image of the GLCM were between 4 and 5. This parameter defines 'imaginary symmetric lines' from the top right corner to lower left corner. Elements located further from these 'imaginary symmetric lines' play more important roles in the textural features or symmetric properties of the bone.

In figure 7, the sum of μ_x, μ_y equals 9.32. Because of this, the 'imaginary symmetric line' (red line) are located a little closer to lower left corner. The first point (the red circle) which is also the farthest point plays the most important role in the Cluster Shade of this matrix and leads the value of total Cluster Shade to -10.27.

Generally, if more shades appear in the top left corner, the Cluster Shade value will be more negative. Relatively, the lower right corner tends to be more positive. This may be the reason why Cluster Shade fits better with bone images than other parameters obtained from the GLCM matrix, because other parameters are positive. More quantization levels provide larger absolute values of Cluster Shade. Cluster Shade also depends on the "spread" of the matrix value away from the diagonal. Based on the analysis, the behavior of this "spread" of the GLCM matrix highly correlates to real world bone's micro-architectural properties.

It is important to note the limitations of this study. The purpose of this study was to apply texture analysis to simulated Dual-energy X-ray Absorptiometry (DXA) scans of trabecular bone and identify the correlation between texture parameters and microarchitecture parameters of trabecular bone. In the clinical situations, DXA has been the gold standard for the diagnosis of osteoporosis and prediction of bone fractures by measuring the bone mineral density (BMD) at the hip, spine and distal wrist. However, BMD measured by DXA cannot account for other factors of bone fractures. Additional information, such as microarchitecture of trabecular bone, is needed to improve the prediction of osteoporotic fractures. Although 3D Micro-CT images of trabecular bone are available to measure the microarchitecture of trabecular bone, the high radiation dose of Micro-CT makes it not practical in the clinical applications. In this study, therefore, we have created 2D projection images from 3D Micro-CT images of trabecular bone to simulate DXA scans. The

correlation between texture parameters of 2D projection images and microarchitecture parameters of trabecular bone is able to justify that such texture analysis will have significance in clinical applications such as DXA scans. We will apply texture analysis in two-dimensional images of DXA scans and three-dimensional images of trabecular bone in the future studies.

4. Conclusion

Dual energy X-ray absorptiometry (DXA) is currently the clinical tool of first choice for measuring bone mineral density (BMD) and for making clinical decisions of osteoporosis patients. Bone mineral density (BMD) assessed by DXA, is not sufficient to account for all spectrums of fracture risks. Current techniques for quantifying the inhomogeneity consists of descriptive statics such as mean, standard deviation and coefficient of variation. However, these parameters do not describe the spatial variation of bone properties. In this study, a novel stochastic method is proposed to describe the spatial variation of bone properties by quantifying the map of BMD derived from 2D images. Once the principle thesis of utilizing second-order statistical texture measures is established, it can be extended to other modalities. This will provide major advantages since, it would be cost effective as most hospitals already have DXA machines and there would be no need for purchasing new equipment. Further, it would be convenient for patients and doctors because of the ready availability of this equipment.

This study has statistically correlated texture features computed from Gray Level Co-occurrence Matrices derived from bone images, with ground truth parameter data from bone samples. The results reveal strong relationships between the computed second-order statistical measures with bone's microstructure properties. Based on comprehensive regression analysis for a number of textural features with real mechanical data, it can be seen that Cluster Shade provides the best correlation with bone features. The linear regression testing showed a high "Coefficient of Determination R^2 " value for this feature, and a close fit with one of the bone's most important microstructure parameters called Bone Volume Fraction BV/TV. A high correlation was also noted between this feature and the bone mechanical properties of elastic modulus and bone strength.

The results from GLCM feature analysis demonstrate that it is possible to estimate bone's microstructure and mechanical properties with 'Cluster Shade'. In summary, the GLCM based Cluster Shade proved to be an effective method of predicting three dimensional bone's microstructure from two dimensional projection images, specifically with bone volume fraction (BV/TV). Discovering these methods is very important because it provides a very convenient and economic solution to predicting bone quality for medical applications such as osteoporosis.

The intent of this paper is to focus on a novel approach to the problem using GLCM and present the results obtained using this approach. It will be worthwhile to present a comparative analysis with the popular semivariogram approach in the future. Specifically, preliminary results comparing the two methods, cluster shade from GLCM provides an excellent fit with bone volume fraction data, which is an important parameter related to the

microstructure of bone. On the other hand, the “sill” extracted from the semivariogram provides a strong method for prediction of the strength and elastic modulus of bone³⁶.

In the future, other texture algorithms such as gray-level difference vector³⁹, max-min texture⁴⁰, Fourier power spectrum⁴¹ can be studied. Studies such as this one can form the basis for the formation of models of bone structure.

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Fig. 1.
Transformation of 3D image into a 2D projection image

Fig. 2.

(a) Gray scale image of 2D projection bone (b) template binary image with “0” inside interest region (c) binary template image after filling process, white stands for valid bone region

Fig. 3.

(a) Original bone image (b) histogram equalization for the whole image (c) histogram equalization only on the valid bone part

(a)

(b)

Fig. 4. Linear regression models for bone parameter Elastic Modulus and (a) Energy $R^2 = 0.395$ and (b) Homogeneity $R^2 = 0.401$.

Fig 5.
 R^2 values for bone parameters with respect to GLCM features when $d=1$ and the four directional results are averaged

Fig. 6.
“Coefficient of Determination R^2 ” for bone volume fraction BV/TV with respect to GLCM measure Cluster Shade when $d=4$ and orientation = 0°

1233	265	97	76	65	60	39	14
380	552	404	316	256	188	108	82
127	467	574	422	371	281	184	163
61	370	400	322	357	362	239	193
36	284	384	338	384	406	372	295
27	200	373	352	428	439	382	434
20	94	218	253	331	432	489	577
14	43	127	214	301	461	598	837

Fig. 7.

GLC Matrix for bone with low Strength for 0.9 Mpa (displacement for 4, quantization levels 8, orientation 90 degrees).

Table 1

Energy and Homogeneity GLCM feature values for each bone sample (displacement 1, orientation 0°) and the coefficient of determination R^2 for bone parameter Elastic Modulus

Image Number	Elastic Modulus (MPa)	Energy	Homogeneity
1	126.0714	0.0662	0.8306
2	226.4135	0.0651	0.8269
3	119.7225	0.0647	0.8257
4	693.0832	0.0551	0.7757
5	552.2352	0.0674	0.8348
6	516.5530	0.0596	0.8010
7	427.3481	0.0595	0.7981
8	534.8067	0.0707	0.8532
9	1224.1589	0.0609	0.8095
10	1511.5544	0.0507	0.7496
11	1722.0936	0.0545	0.7696
12	1604.3418	0.0611	0.8064
13	1028.7697	0.0523	0.7576
R^2		0.395	0.401

Table 2

Coefficient of Determination R^2 values for bone parameter Elastic Modulus, for GLCM parameters Energy, Entropy, Contrast, Homogeneity, Correlation and Autocorrelation with displacement = 1 and orientation = 0° .

R^2 (Elastic Modulus)	d=1	d=2	d=3	d=4	Average
Energy	0.395	0.412	0.409	0.393	0.402
Entropy	0.45	0.45	0.447	0.434	0.445
Contrast	0.456	0.481	0.502	0.503	0.489
Homogeneity	0.401	0.41	0.424	0.429	0.416
Correlation	10.394	0.48	0.507	0.51	0.473
Autocorrelation	0.316	0.498	0.54	0.568	0.481

Table 3

Bone volume fraction BV/TV fit with GLCM feature Cluster Shade for various displacements and orientations

R^2 (BV/TV)	d=1	d=2	d=3	d=4
0 degrees	0.26	0.703	0.855	0.879
45 degrees	0.609	0.695	0.655	0.628
90 degrees	0.43	0.701	0.733	0.704
135 degrees	0.46	0.794	0.852	0.838
Average	0.44	0.723	0.774	0.762

Table 4

Cluster Shade GLCM feature values for each bone sample (displacement = 2) and the coefficients of determination R^2 for bone parameter bone volume fraction (BV/TV) for different orientations

BV/TV	Shade (0°)	Cluster Shade (45°)	Cluster Shade (90°)	Cluster Shade (135°)
0.135896	-4.544	-6.491	-6.584	-7.418
0.147494	-3.115	-4.504	-4.893	-5.215
0.131742	-3.349	-9.268	-5.988	-3.345
0.16612	-4.513	-5.720	-5.820	-5.624
0.257839	-2.594	-0.732	-0.616	-0.325
0.186335	-1.954	-1.619	-2.618	-3.265
0.198986	-2.921	-3.537	-1.992	-2.450
0.223	-2.776	-3.184	-2.853	-3.092
0.21531	-2.397	-2.258	-2.179	-2.285
0.232785	-1.491	-1.032	-0.535	-1.522
0.334365	-0.697	-0.617	-1.285	0.643
0.306089	-0.468	-0.138	-0.421	0.661
0.286095	-1.912	-1.839	-1.860	-1.144
R^2	0.703	0.695	0.701	0.794

Table 5

Bone Elastic Modulus fit with GLCM feature Cluster Shade for various displacements and orientations

R^2 (Elastic Modulus)	d=1	d=2	d=3	d=4
0 degrees	0.336	0.647	0.687	0.68
45 degrees	0.571	0.542	0.478	0.445
90 degrees	0.442	0.521	0.501	0.447
135 degrees	0.422	0.544	0.571	0.552
Average	0.442	0.564	0.557	0.531

Table 6

Bone Strength fit with GLCM feature Cluster Shade for various displacements and orientations

R^2 (Strength)	d=1	d=2	d=3	d=4
0 degrees	0.316	0.678	0.728	0.706
45 degrees	0.58	0.583	0.519	0.478
90 degrees	0.433	0.569	0.565	0.541
135 degrees	0.436	0.6	0.624	0.588
Average	0.441	0.608	0.609	0.578