Computer Aided Diagnosis of Osteoporosis Using 1st Order Texture Parameters

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ABSTRACT

Osteoporosis is a medical condition in which the bone loses minerals such as calcium and phosphate. This results in reduction of bone mineral density by which it becomes brittle and fragile leading to breakage. 1 in 3 women and 1 in 5 men aged 50 are found to experience osteoporotic fracture. Causes of osteoporosis take in hormonal imbalance, lack of calcium and vitamin D, thyroid conditions, sedentary lifestyles. Early diagnosis of the disease can effectively predict fracture risk and prevent the disease. Imaging modalities like CT, MRI, X-ray are used for diagnosis. The assessment of bone mineral density (BMD) is very critical for the diagnosis of the disease. Visual interpretation of x-ray image to classify between the normal and osteoporotic bone is highly inaccurate. We used 1st order texture parameters for the diagnosis of osteoporosis. This method includes the calculation of various parameters using x-ray images of both normal and osteoporotic bone. The results obtained show that the proposed method could be used for early diagnosis of osteoporosis using x-ray images.

Keywords - **Detection, Osteoporosis, Bone mineral density(BMD), 1st order texture parameters.**

I. INTRODUCTION

Bone supports and protects the organs of the body. It produces RBC's & WBC's ,stores minerals and enable mobility for the body. Bone is an active tissue which is composed of different types of bone cells. Osteoblasts are associated with creation & mineralization.
Osteocytes and osteoclasts are associated with reabsorption of the bone tissue. Osteoporosis is a disease that affects the bones where it becomes brittle and fragile from loss of tissues and reduction in bone mass. Decrease in bone strength increases the risk of breakage of bones. Worldwide, osteoporosis cause more than 8.9 million fractures per annum ,resulting in an osteoporotic fracture every 3 seconds.1 in 3 women and 1 in 5 men aged 50 are found to experience osteoporotic fracture. the causes of osteoporosis are many like low estrogen in women, low testosterone in men, other hormonal imbalances, lack of calcium, lack of vitamin d, thyroid conditions, smoking, medical conditions ,sedentary life style etc. Osteoporosis-related injuries result in complications leading to prolonged hospitalization, decreased independence, increased incidence of depression, and a reduced quality of life. Osteopenia has been defined as the appearance of decreased bone mineral content on radiography, but the term more appropriately refers to a phase in the continuum from decreased bone mass to fractures and frailty. By the time the diagnosis of osteopenia is made radiographically, significant and irreversible bone loss has already occurred. The main common cause of osteopenia is osteoporosis; other causes include osteomalacia and the bone disease of hyperparathyroidism. The prevention of 'first' osteoporotic fracture is better than its cure, as there are several techniques available for the in-vivo measurement of BMD.

Tejaswi et.al proposed Detection and Prediction of Osteoporosis using Impulse response technique and Artificial Neural Network. Nasrin Afsarimanesh et.al proposed Sensors and Instrumentation towards early detection of Osteoporosis. Vishnu.T et.al proposed Efficient and Early detection of Osteoporosis using Trabecular Region. Sahiti lahari et.al proposed Finite Element Analysis of Femur in the Evaluation of Osteoporosis. Keni Zheng et.al proposed Bone Texture Characterization for Osteoporosis Diagnosis using Digital Radiography. Stefan Wesarg et.al proposed CAD of Osteoporosis in Vertebrae Using Dual-energy CT. D. Lee et.al proposed Preliminary study on monitoring the progression of osteoporosis using UWB radar technique in distal femur model. Abdessamad Tafraouti et.al proposed Osteoporosis Diagnosis using Steerable pyramid Decomposition and Fractional Brownian Motion.

II. INDENTATIONS AND EQUATIONS

The major steps involved in the implementation of this project are as follows:

- Image acquisition
- ROI selection
- Feature extraction

- Feature selection and reduction
- Classification

Image acquisition

Cases of normal and osteoporosis images of varying degrees were confirmed by ultrasound practitioners with years of clinical experience.

ROI selection

After acquiring image, To analyze X ray image characteristics quantitatively, ROI is selected by the examiners

Feature Extraction

Bone surface is treated as a texture and thus various texture parameters are selected to analyze the liver ultrasound images.

Spatial gray-level co-occurrence matrix:

Among all statistical methods, the most popular one which is based on the assessment of the second order statistics of the spatial arrangement of the gray values, is the gray level co-occurrence matrices.
A co-occurrence matrix is a square matrix whose elements match up to the relative frequency of occurrence of pairs of gray level of pixels separated by a certain distance in a given direction.

Haralick, Shanmugan and Dinstein proposed measures of textural features which are
derived from the co-occurrence matrices, and each represents certain image properties as coarseness, contrast, homogeneity and texture complexity.

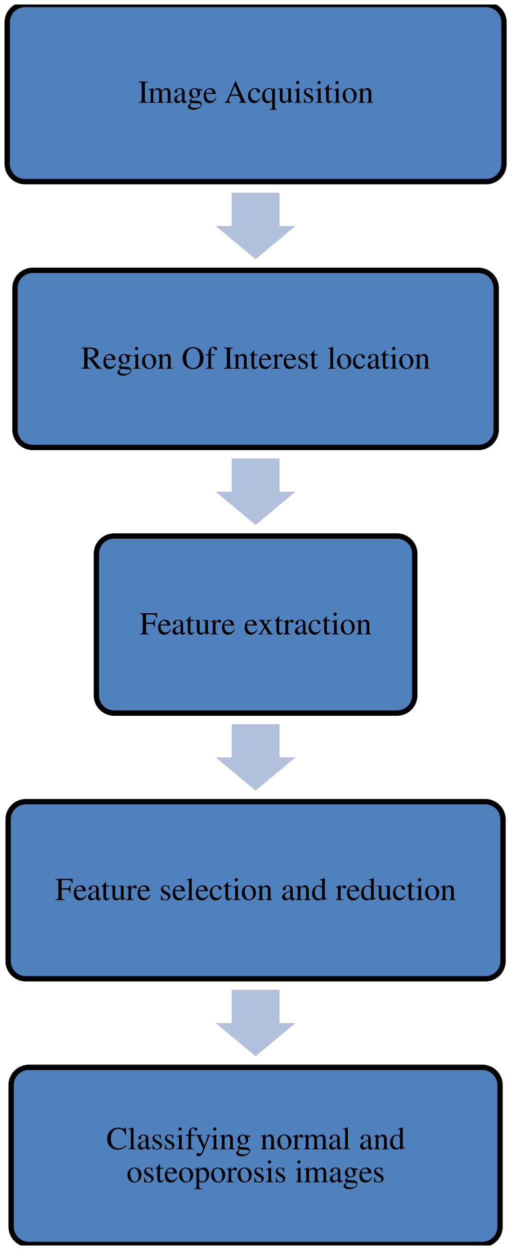

Fig (1) Block diagram

Those that are worn, in this work, to extract features in the defect detection of textured images are:

1) Entropy

$$ent = -\sum_i \sum_j p(i,j) \log p(i,j)$$

Entropy gives a measure of complexity of the image. Complex textures tend to have higher entropy.

2) Contrast

$$con = \sum_i \sum_j (i-j)^2 p(i,j)$$

Contrast feature is a gauge of the image contrast or the amount of local variations present in an image.
$p(i,j)$ refers to the normalized entry of the co-occurrence matrices. That is $p(i,j) = P_d\ (i,j\ )/R$ where R is the total number of pixel pairs (i,j).

3) Energy

Energy $= \sum_i \sum_j p(i,j)^2$

4) Mean

Mean$= \sum_i \sum_j p(i,j)/\mathrm{MN}$

All the Normal and osteoporosis bone images are analyzed quantitatively for 8 texture parameter values.. Finally the highly correlated features are removed and out of the remaining features, only those features are selected which has the high relevance with surface smoothness being evaluated by radiologist subjectively.

III. Figures and Tables

Fig (2) a: Shows the set of normal x-ray images

Fig (2) b: Shows the set of osteoporotic x-ray images

Table2. 1st Order Texture Prameters for osteoporotic x-ray images.

Patient	Mean	Contrast	Energy	Entropy
1.	0.5217	0.1771	0.2464	6.7886
2.	0.5362	0.1344	0.2304	6.9757
3.	0.5792	0.1280	0.3462	6.3648
4.	0.5342	0.1721	0.2660	6.7275
5.	0.5533	0.1620	0.2968	6.9324
6.	0.5778	0.1646	0.2717	6.4831
7.	0.5409	0.1422	0.2604	6.8456
8.	0.5349	0.1080	0.2510	6.9651
9.	0.5053	0.1461	0.2693	6.8464

Table1. 1st Order Texture Prameters for normal x-ray images

Patient	Mean	Contrast	Energy	Entropy
1.	0.9509	0.0149	0.5449	4.3536
2.	0.6124	0.0805	0.4602	5.9633
3.	0.9426	0.0546	0.7044	4.2418
4.	0.6360	0.0740	0.6408	5.2616
5.	0.6841	0.0129	0.5812	4.3530
6.	0.9426	0.0516	0.6240	5.2356
7.	0.9753	0.0458	0.6112	4.2654
8.	0.7565	0.0289	0.7821	4.1543
9.	0.6504	0.0643	0.4068	5.2486

Table 3. Shows Acurracy of the proposed method

IMAGES	TESTED	CLASSIFICATION	ACCURACY
Normal	9	6	66.66%
Abnormal	6	8	88.88%

A set of 9 images of normal x-ray and Osteoporotic X-ray images are taken for analysis. The region of interest was selected and 1st order texture parameters were calculated for the images. The mean, contrast, energy and entropy values of 1st order texture parameters are tabulated. Table 1 shows the texture parameters of normal bone. Table 2 shows the texture parameters of osteoporotic bone. The results obtained from tables indicate large variations in the texture parameters.

Table 3 shows the accuracy of the proposed method. 6 out of 9 normal images are rightly diagnosed and is found to be 66.66% accurate. 8 out of 9 osteoporotic images are rightly diagnosed and is found to be 88.88% accurate. The tabulated results show that the Normal x-ray images have highest mean and energy where as its contrast and entropy are low; Osteoporotic x-ray images have low mean and energy.

IV. CONCLUSION

The texture features can be used for the detection of osteoporosis bone by the results obtained. By analyzing more images of patients of different age group by 1st order texture parameters and the statistical techniques, suitable decision rule can be found in future.

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