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Research Article

Research on Law's Mask Texture Analysis System Reliability

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Abstract: Texture analysis of X-ray bone image using Laws' mask for direct evaluation of the bone quality has been popular. Nevertheless, detailed reliability evaluation of the system classification has been relatively unknown. In this study, we will examine the reliability of the Laws' mask system classification by using the confusion matrix approach. The precise detection system by using standard deviation statistical descriptor is supported by the true positive of 87.5% and true negative of 83.33%. In conclusion, the statistical analysis of the texture based osteoporosis detection system's reliability discloses a true potential in this detection technique. Nevertheless, future researches should include a larger image database to enhance the reliability of the results.

Keywords: Confusion matrix, osteoporosis, statistical descriptor, texture

INTRODUCTION

The occurrence of osteoporosis is unpredictable, characterized by its silent progression and deadly aftermaths. Osteoporosis is typically specified by low bone density and micro-architectural deterioration and consequently leads to fragility in bone strength as well as susceptibility to fracture (Bauer and Link, 2009; Eastell, 2005; Hong Seng and Tian Swee, 2013a). The low bone density is defined by the excessive rate of bone resorption over the rate of bone formation. Among the prominent factor that contributes to the loss of bone strength is age. As people ages, the bone strength is reduced subsequently, caused by the bone mass loss. As a result, the cortical bone becomes thinner while the trabecular bone becomes looser.

Bone Mineral Density (BMD) is the indirect measurement approach for osteoporosis, yet representing current gold standard for osteoporosis evaluation. Generally, BMD measurement is based on the absolute value called T score. T score is the number of standard deviation at which the indicated values reflect the mass density condition of the bone. According to World Health Organization (WHO), there are three classes of T score evaluations. The T score of normal population should lies above the value of -1. On the other hand, osteopenia (prelude to osteoporosis) ranges between -1 and -2.5 while osteoporosis population would have a T score below -2.5 (Bauer and Link, 2009).

In medical image processing technique, Law's Mask (Laws, 1980) has received wide acceptance in the medical image analysis. Kenneth Ivan Laws brought forward the Laws' masks idea in 1980, where the main contribution of his approach has been the filtering of images with specific masks created from the combination of one dimensional Kernel vector in order to assess the texture properties. The Laws' masks match the pixel neighborhood to the set of standard masks to compute the texture properties of images.

There are five types of masks, namely Level (L), Edge (E), Spot (S), Ripple (R) and Wave (W). In addition, this image processing technique could be further divided into 5×5 dimensions and 3×3 dimensions. The level vector demonstrates the average grey level or center weighted local average; edge vector resembles the gradient operator, responds to the column and row stepped edges in an images; spot vector represents the spot extraction; ripples vector detects ripple from the image while wave vector responds to any image pixel changes. Thus, 25 possible combinations of different masks are produced, with each combination serves equal potential in unlocking the highly discriminative information describing the bone quality and condition.

In this study, we propose to initiate a research on the reliability of the 5×5 dimension Laws' Mask texture analysis using the confusion matrix. The result of this experiment will contribute to the characterization accuracy of osteoporosis feature through appropriate classification criterions. Two statistical descriptors

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namely mean and standard deviation will reflect the accuracies of the system developed based on the concept of Laws' mask.

Overview of the evaluation of system reliability: Through mean statistical descriptor and standard deviation statistical descriptor, we have conducted the statistical evaluation to examine the reliability of the system for future osteoporosis detection using Laws' masks technique. The mathematical formulas for the mean and standard deviation statistical descriptor computed in this experiment have been illustrated in Eq. (1) and (2) (Hong Seng and Tian Swee, 2013b):

$$Mean = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}\left[TR_{i,j}\right]}{M \times N} \tag{1}$$

$$SD = \sqrt{\frac{\sum_{i=0}^{M}\sum_{j=0}^{N}\left[TR_{i,j} - Mean\right]^2}{M \times N}} \tag{2}$$

METHODOLOGY

Development of osteoporosis texture analysis model: Using six normal X-ray and one osteoporosis X-ray image, the image contrast is enhanced using histogram equalization and resized. The desired features are extracted and parameterized through texture analysis. A window size of 15 pixels is applied. We apply 5×5 dimension Laws' Mask, producing a total of 25 masks. Table 1 illustrates the one dimension convolution kernel of length 5 and Table 2 illustrates all 25 mask combinations generated in this experiment. Next, the image is texturally analyzed according to selected features. Finally, the data is clustered by using the Euclidean distance based clustering.

Histogram equalization of X-ray images: Histogram equalization has been applied in numerous fields, for example, computerized medical intervention (Gonzalez and Woods, 2007), medical image analysis (Yan Chai *et al*., 2013), image document processing, LCD display processing and radar. Because our experiment is not emphasizing on the contrast enhancement, we would briefly explain the enhancement technique utilized in this study.

The contrast between background and bone is already very similar. Therefore, we have selected to locally modify the histogram of X-ray image. Local histogram equalization is capable of preserving the local brightness feature by using small window specified for certain regions of interest. The windowing operation will filter the pixels and allows only blocks of pixels that fulfill the criterion of the specific window (Wang and Zhongfu, 2005; Chauhan and Bhadoria, 2011; Menotti *et al*., 2007; Rajavel, 2010; Gonzalez and Woods, 2007).

Table 1: The one dimension convolution kernel of length 5

Kernel	Matrices
L_5	(1 4 6 4 1)
E_5	(-1 -2 0 2 1)
S_5	(-1 0 2 0 -1)
R_5	(1 -4 6 -4 1)
W_5	(-1 2 0 -2 -1)

Table 2: The generation of 25 different mask combination of 5×5 dimension laws' mask

L_5L_5	L_5E_5	L_5S_5	L_5R_5	L_5W_5
E_5L_5	E_5E_5	E_5S_5	E_5R_5	E_5W_5
S_5L_5	S_5E_5	S_5S_5	S_5R_5	S_5W_5
W_5L_5	W_5E_5	W_5S_5	W_5R_5	W_5W_5
R_5L_5	R_5E_5	R_5S_5	R_5R_5	R_5W_5

The histogram with intensity level (0, L - 1) of the image is the adjusted histogram range. The normalized range could be obtained by normalizing the number of pixel with intensity r_k, n_k with the total number of pixel, N in the X-ray image, where the mathematical expression of the histogram normalization, p (n_k) is shown in Eq. (3). The normalized histogram represents an estimate of the likelihood of intensity level n_k to occur in the X-ray image (Gonzalez and Woods, 2007):

$$p(r_k) = \frac{n_k}{N} \tag{3}$$

In this experiment, we view the input intensity variable, r in the X-ray image as random variables in the interval of (0, L - 1). The output of the intensity variable, s can be produced through transformational function, T (r). The transformation is illustrated in Eq. (4). Next, we would descript the random variable through Probability Density Function (PDF), in which the input intensity variable r and the transformed intensity s are contributing to the PDF of the transformed variable s shown in Eq. (5):

$$s = T(r) = (L-1)\int_0^r p_r(w)dw \tag{4}$$

$$p_s(s) = p_r(r)\left|\frac{dr}{ds}\right| \tag{5}$$

Laws' masks texture analysis: Image texture exhibits spatial information regarding the intensity or color of the image (Tuceryan and Jain, 1998; Davies, 2008). Statistical techniques such as Law's mask, edge detection and Grey level co-occurrence matrix (Clausi, 2002) are popular because these methods are simple to be applied (Bharati *et al*., 2004) into the image processing procedure.

Derived from the concept of texture energy defined at each pixel after a series of particular convolution with selected mask, Laws' Mask can produce the texture energy measurement for the analysis of the texture property of each pixel (Rachidi *et al*., 2008a, b). The two 2-dimensioanl convolution kernels, generated from different combinations of the 5 masks, are applied onto the converted gray scale image, which comprises of four ROIs. The image $I_{i,j}$ is assumed to have a size of N rows and M columns. After the filtration, say by a 2D mask L_5L_5, the image is recognized as a texture image, T_1 and will have an image dimension of N+1×M+1. The texture image is descripted in Eq. (6):

$$TL_5L_5 = I_{i,j} \times (L_5L_5) \tag{6}$$

According to Laws, only texture image TI_5I_5 and $TI_{E_3E_3}$ can normalize the contrast of all texture image TI_{ij} because these two 2D mask combinations have zero mean compare to other (Rachidi, 2008). As a result, the result produced by these mask combination will depend heavily on image intensity rather than texture.

We will perform the windowing operation. The image passes through the Texture Energy Measure (TEM) to replace every pixel of the image by comparing the pixel with its local neighborhood and subsequently sum up the absolute values from the neighboring pixel. The operation will lead to the creation of TEM image and descripted in Eq. (7):

$$TEM_{i,j} = \sum_{u=-7}^{7}\sum_{v=-7}^{7}\left|TI_{(i+u,j+v)}\right| \tag{7}$$

After the windowing operation, we will normalize the features for the contrast of all the obtained images in order to be presented appropriately as image. All convolution kernels are zero-mean except for L_5L_5, where the normalized kernels are descripted in Eq. (8):

$$Normalized(TI_{mask}) = \frac{TI_{(i,j)mask}}{TI_{(i,j)L_5L_5}} \tag{8}$$

Lastly, we will combine the TEM descriptors to eliminate a dimensionality bias from features. Because TEM_{L5E5} been found to be sensitive to changes in vertical edges while TEM_{E5L5} is sensitive to changes in horizontal edges, a single feature that is sensitive to simple edge content could be obtained by adding these two descriptors. The mathematical operations for the additional of these two descriptors are computed in Eq. (9):

$$TR_{E5L5} = \frac{TEM_{L5E5} + TEM_{E5L5}}{2} \tag{9}$$

Euclidean distance-based clustering: We have conducted cluster analysis in pattern recognition stage. Cluster analysis focuses primarily on assigning different set of objects with certain degree of similarities into their assigned group (cluster) (Zhan-Ao *et al*., 2008; Daxin *et al*., 2010). Cluster analysis enables us to identify the relationship between different clusters.

The Euclidean distance based clustering represents the grouping of a set of data based on the distance measurement as shown (Danielsson, 1980). The definition of Euclidean distance measurement is illustrated in Eq. (10), where the x_i is the mean value of testing input image and x is the standard mean value of the training set images. For instance, two data point is computed using square root of the sum of the squares for the difference between these two corresponding values based on the Pythagoras theorem, which studied the geometry relationship between the sides of a triangle:

$$d(x_i, x) = \sqrt{\sum_{i=1}^{n}(x_i - x)^2} \tag{10}$$

In our experiment, we assume the output distance that is shorter than our threshold distance to be the same cluster and the classification is divided into two classes i.e., healthy and osteoporosis. Thus, an image is classified as healthy if the distance value computed is smaller compared to that of the osteoporosis bone image.

We repeat the procedure when measuring the standard deviation descriptor. Nevertheless, the mean value of healthy bone image is lower than osteoporosis image while in the case of standard deviation, the osteoporosis image will render a higher value compared to healthy image. The higher standard deviation demonstrated by osteoporosis image is largely due to the reason that the pixel value of osteoporosis image is lower, contributing to larger deviation from its mean value.

Confusion matrix: Conventional reliability of the developed system has been determined by using the simple yet unreliable classification metric such as accuracy. For instance, the accuracy fails in the presence of large number of varying samples derived from different classes. The confusion matrix, on the other hand, offers much detailed statistical analysis on the true reliability of the system. The matrix discloses the number of actual results that match the predicted results.

There are two main elements that made up of the confusion matrix table i.e., actual and predicted classes with 4 possible outcomes. Table 3 depicts the general formulation of confusion matrix. In particular, the terms

Table 3: General confusion matrix used in statistical validation for various types of experiments

		Predicted	
		Negative	Positive
Actual	Negative	a	b
	Positive	c	d

negative and positive refer to the decision produced by Law's Mask, where "a" in the general confusion matrix indicates correct prediction that an instance is positive, "b" indicates the number of incorrect predictions that an instance is negative, "c" indicates the number of incorrect predictions that an instance is positive and "d" indicates the number of correct predictions that an instance is negative. There are four outcomes which are defined within the context of confusion matrix, commonly known as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) (Hong Seng and Tian Swee, 2013a).

The mathematical expressions for all four possible outcomes are illustrated in Eq. (11) to (14). If the positive and negative predictions are correctly matched by the actual incidents, that the situation is recognized as true positive and true negative, respectively. In the case where the actual class is a "yes" but the predicted class has been wrongly classified as "no", then the result is considered false negative. The same case applies for false positive:

$$TP = \frac{d}{c+d} \tag{11}$$

$$TN = \frac{a}{a+b} \tag{12}$$

$$TP = \frac{b}{a+b} \tag{13}$$

$$TP = \frac{c}{c+d} \tag{14}$$

Meanwhile, the precision and the accuracy of the system can be computed through confusion matrix as well, in which the mathematical expression of these two elements are illustrated in Eq. (15) and (16):

$$Accuracy = \frac{a+d}{a+b+c+d} \tag{15}$$

$$\Pr ecision = \frac{a}{a+c} \tag{16}$$

RESEARCH ON LAW'S MASK TEXTURE ANALYSIS SYSTEM RELIABILITY BASED ON CONFUSION MATRIX

In 1986, a new texture measure that is related to a set of orientated sensitive windows is developed. The objective of his study has been focusing on evaluating the non-uniformity of the intensity within a set of locally directed neighborhood surrounding a pixel and followed by the first order statistic computational of the variance measure within a large windows. Besides, global orientation sensitivities of the individual texture measures were considered and results in a better outcome. However, the shortcoming of this method lies with the limited number of texture samples.

In the following year, the use of adaptive mask is suggested instead of a fixed mask convolution. Based on his suggestion that the mask could be tuned in search of a better feature, he included the learning mechanism. Although the method improves the reliability of the Laws' mask texture considerably, the introduction of learning mechanism invariably increase the computational complexity when adjusting the mask elements (Srinivasan and Shobha, 2008) slowing down the whole detection system.

The confusion matrix approach has been introduced in order to assess the reliability of the texture analysis system for osteoporosis detection. In this study, we treat positive as healthy image class while negative as osteoporosis image class. The results are compared by using the mean and standard deviation statistical analysis in order to determine a suitable statistical analysis descriptor for the system. The decision is based on the accuracy and precision obtained from the system.

From Table 4, the recorded reliability of the system based on mean statistical analysis is rendering mediocre assessment result. The system is capable of recognizing the osteoporosis image by 50% and healthy image by 83.33% while the accuracy of the system stands at 66.67%. A much detailed statistical analysis indicated the capability of mean statistical descriptor to differentiate healthy and osteoporosis images stands at 62.5% in classifying the healthy images and 75% in classifying the osteoporosis images.

Meanwhile, from Table 5, the standard deviation statistical analysis is considered as a better selection with the precision of identifying healthy images of

Table 4: Confusion matrix for mean statistical analysis with the accuracy and precision computed using above mentioned mathematical equation

		Predicted	
		Positive	Negative
Actual	Positive	15	9
	Negative	3	9
TP	TN	FP	FN
62.5%	75%	25%	37.5%

The latter four statistical results represent the four possible outcomes i.e., TP, TN, FP, FN

Table 5: Confusion matrix for standard deviation statistical analysis with the accuracy and precision computed using above mentioned mathematical equation

		Predicted	
		Positive	Negative
Actual	Positive	21	3
	Negative	2	10
TP	TN	FP	FN
87.5%	83.33%	16.67%	12.5%

The latter four statistical results represent the four possible outcomes i.e., TP, TN, FP, FN

91.30% and osteoporosis of 76.92%. The accuracy of the overall system, obtained by combining both true positive and true negative data, is 86.11%. We have observed the high reliability of recognizing the correct healthy images where 87.5% of the healthy images are being classified correctly. Furthermore, 83.33% of the osteoporosis images have been correctly identified. The standard deviation statistical analysis improves the classification statistical descriptor for the system in both the healthy and osteoporosis cases.

Quantitatively, the TN and TF for the standard deviation statistical descriptor is 83.33 and 87.5% against 75 and 62.5%, respectively for mean statistical descriptor. While the TN and TF for standard deviation statistical descriptor is higher, both statistical descriptors are rendering considerably satisfying results for this stage of experiment. The relatively high TN and TF rates using mean statistical descriptor and standard deviation statistical descriptor in classifying the healthy and osteoporosis images indicate the true potential of Laws' mask technique to directly analyze the texture of bone through X-ray images. Moreover, our experiment contributes to identifying the more appropriate statistical descriptor in classification of the texture analysis of musculoskeletal study (Yan Chai *et al*., 2013; Hong Seng and Tian Swee, 2013a, b) as few experiments have been dedicated to the statistical validation of the texture analysis system.

CONCLUSION

In this study, we focus on the reliability computational of the system. In order to assess the reliability of the overall texture analysis system for osteoporosis detection, we have demonstrated a detailed statistical description using confusion matrix. The mean statistical descriptor has been demonstrating lower overall accuracy and precision in identifying both the healthy and osteoporosis images compared with standard deviation statistical descriptor.

Our findings suggest the application of the standard deviation statistical descriptor in future researches for developing the Law's Mask technique for osteoporosis detection. Besides, we also recommend that future researchers need to increase the number of images included in their experiment as this is currently a drawbacks in our experiment. Furthermore, more statistical analysis parameters such as sensitivity, specificity, entropy, skewness and kurtosis should be included in future research for developing the texture analysis for osteoporosis prevention.

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