Computer Aided Diagnosis of Digital Mammograms

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Abstract- **The high incidence of breast cancer in women has increased significantly in the recent years. Mammogram – breast x-ray imaging – is considered the most effective, low cost, and reliable method in early detection of breast cancer. Although general rules for the differentiation between benign and malignant breast lesion exist, only 15 to 30% of masses referred for surgical biopsy are actually malignant. Physician experience of detecting breast cancer can be assisted by using some computerized feature extraction algorithms. We are introducing, as an aid to radiologists, a computer diagnosis system, which could be helpful in diagnosing abnormalities faster than traditional screening program without the drawback attribute to human factors. The techniques used in this paper for feature extraction is based on the invariant features and fractal dimensions of locally processed image (ROI). Two statistical classifiers (The minimum distance classifier and the voting K-Nearest Neighbor classifier) were used and compared through the system to reach a better classification decision.**

Index Terms- **CAD, Mammography, Feature extraction, Invariant, Fractals, Classifier.**

I. INTRODUCTION

Breast cancer is one of the most significant public health problems in the world. It is a leading cause of fatality among all cancers for women in the 35 to 55 age group. Until now there is no known way to prevent breast cancer but the earlier the cancer is detected, the higher the chance of survival for patients. Mammography is the most effective method that is used in the early detection of breast cancer [1], [2].

It may not be feasible to routinely perform a second reading by a radiologist due to financial, technical, and logistical restraints. Therefore, efforts were made to develop a computer-aided detection (CAD) system [3], [4]. CAD can be defined as a diagnosis made to improve radiologists' performance by indicating the sites of potential abnormalities, to reduce the number of missed lesions, and/or by providing quantitative analysis of specific regions in an image to improve diagnosis. CAD systems typically operate as automated "second-opinion" or "double reading" systems [5].

Many techniques have been used to detect masses in the mammograms. Youssry et al. [6] used a technique that depends on the difference between normal and cancerous histograms and used four statistical features for the classification process through a neural network classifier. The four features are the mean and the first three moments. He used histogram equalization and segmentation as preprocessing techniques.

Yu et al. [1] proposed a CAD system for the automatic detection of clustered microcalcifications through two steps. The first one is to segment potential microcalcification pixels by using wavelet and gray level statistical features and to connect them into potential individual microcalcification objects. The second step is to check these potential objects by using 31 statistical features. Neural network classifiers were used. Results are satisfactory but not highly guaranteed because the training set was used in the testing set.

Brake et al. [7] studied single and multiscale detection of masses in digital mammograms. Scale is an important issue in the automated detection of masses in mammograms, due to the range of possible sizes masses can have. In this work, it was examined if detection of masses can be done at a single scale, or whether it is more appropriate to use the output of the detection method at different scales in a multiscale scheme.

Nakayama et al. [8] used a filter bank for the detection of nodular and linear patterns. The filter bank is designed so that the subimages generated the elements of a Hessian matrix at each resolution level. By calculating the small and large eigenvalues, a new filter bank has the following three properties. (I) Nodular patterns of various sizes can be enhanced. (II) Both nodular and linear patterns of various sizes can be enhanced. (III) The original image can be reconstructed with these patterns removed. The filter bank is applied to enhance microcalcifications in mammograms.

Karssemeijer [9] developed a statistical method for detection of microcalcifications in digital mammograms. The method is based on the use of statistical models and the general framework of Bayesian image analysis. Chan et al. [10] investigated a computer-based method for the detection of microcalcification in digital mammograms. The method is based on a difference image technique in which a signal suppressed image is subtracted from a signal enhanced image to remove structured background in the mammogram. Global and local thresholding techniques are then used to extract potential microcalcification signals.

Abou-Chadi et al. [6] used a neural network approach for detecting candidate circumscribed lesions in digitized mammograms. The neural network trained using back propagation algorithms. The procedure depends mainly on the major difference between the histogram of the normal tissue and that of the cancerous tissue.

In this paper, we propose a CAD system for detecting abnormalities in the digitized mammograms. This study is done through two main phases; the training phase and the testing phase. First in the training phase, the system is trained how to differentiate between normal and cancerous cases by using predefined normal and cancerous images. Then in the testing phase, we test the performance of the

system by entering a test image to compute the correctness degree of the system decision.

The main objective of our work is to clarify the usefulness of using the fractal features (as a texture scale-invariant features) to classify normal and cancerous images. We showed that in three steps, in the first two steps we did not use any preprocessing techniques such as smoothing, edge sharpening, or wavelet decomposition. We just dealt with the mammograms as raw data without any alteration in it. The first step was classification of images without fractal features. Then, in the next step we classify with all features (but without any enhancement). The third step we included the fractal features but after preprocessing. Fig.1. shows the block diagram for the proposed CAD system.

II. BACKGROUND

Fractal Analysis:

Traditionally the Euclidean objects [11], such as lines, planes, and circles etc., have used as the basis of the intuitive understanding of the geometry of nature. However, most nature objects do not resemble Euclidean objects. Fractal geometry made it possible to model nature objects to a better description in many conditions. The concept of fractal was first introduced by Mandelbrot [12]. The main distinct difference between Euclidean and fractal geometry is that of self-similarity which is described by nonuniform scaling. In theory, shapes of fractal objects keep invariant under successive magnifying or shrinking the objects. We have known that the texture is a problem of scale, and the texture description is scale dependent. Hence, using fractal geometry can overcome the scale problem of texture. Because the concept of fractal dimension is an indicator of the surface roughness, people usually describe texture as fine, coarse, gained, and smooth, etc. Hence, it implies that fractal-based texture analysis is a correlation between texture coarseness.

A variety of procedures, including box-counting, fractal Brownian motion [13-14], and fractal interpolation function system [11], have been proposed for estimating the fractal dimension of images. The fractional Brownian motion model with gray-scale variation [13-14] has been shown promise in the medical image texture. The Brownian motion curve concepts can be extended to the fractional Brownian motion curve $I(x)$, and $|I(x_2)-I(x_1)|$ have a mean value proportional to $|(x_2-x_1)|^H$. Thus, in the fractal Brownian motion there is only one parameter of interest, H, or the Hurst coefficient, which can be described as texture features when we applied to classify breast tumor images. Considering the topological dimension T_d, for images, $T_d=3$, the fractal dimension D can be estimated from the Hurst coefficient $H = T_d - D$.

For the medical images, the fractal dimension can be estimated from the above relationship. For an MxM image I, the implementation of estimation fractal dimension [13] can be defined as

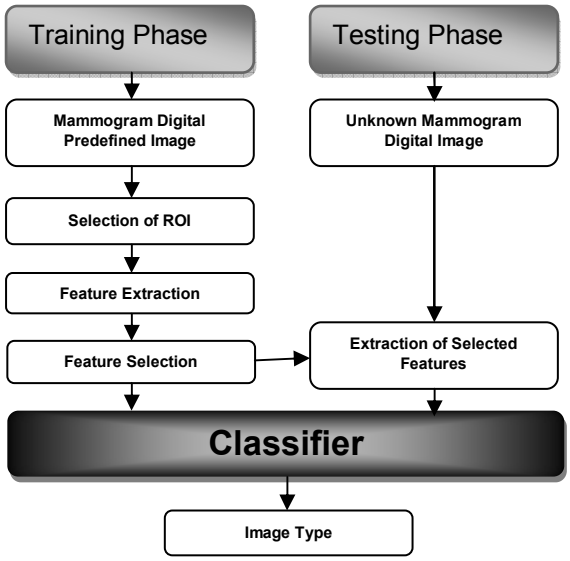

Fig.1. Block diagram for the CAD system.

$$di(k) = \frac{\sum_{x1=0}^{M-1}\sum_{y1=0}^{M-1}\sum_{x2=0}^{M-1}\sum_{y2=0}^{M-1}|I(x2,y2)-I(x1,y1)|}{Pn(k)} \quad (1)$$

where $Pn(k)$ is total number of pixel pairs with distance

$$\Delta r_k = \sqrt{(X_2-X_1)^2+(Y_2-Y_1)^2} \quad (2)$$

and

$$f(k) = log(di(k)) - log(di(1)) \quad (3)$$

for k = 1, 2, ... , n.

The vector *[di(1), di(2), ..., di(n)]* is called the multiscale intensity difference (MSID) vector and the vector *[f(1), f(2), ..., f(n)]* is called the factional Brownian motion feature (FBM) vector. Fractal dimension D is then derived from the values of the Hurst coefficients. A small value of the fractal dimension, i.e. a large value of H, represents a fine texture, while a large fractal dimension corresponds to a coarse texture. However, the drawback of the Eq. (1) tends to be time consume, this algorithm needs M^4 operations for estimating the fractal dimension of an image of size MxM. Thus, Chen et al., [14] proposed another modified method using the gray level differences between the pixel pairs with horizontal, vertical, diagonal, and asymmetric-diagonal directions. The $di(k)$ is redefined as,

$$di(k) = \left[\begin{array}{l} \sum_{x=0}^{M-1}\sum_{y=0}^{M-k-1}|I(x,y)-I(x,y+k)|/M(M-k) \\ +\sum_{y=0}^{M-1}\sum_{x=0}^{M-k-1}|I(x,y)-I(x+k,y)|/M(M-k) \\ +\sum_{x=0}^{M-k-1}\sum_{y=0}^{M-k-1}|I(x,y)-I(x+,y+k)|/(M-k)^2 \\ +\sum_{x=0}^{M-k-1}\sum_{y=0}^{M-k-1}|I(x,M-y)-I(x+k,M-(y+k))|/(M-k)^2 \end{array}\right] / 4 \quad (4)$$

As we all know, the fractal analysis is sensitive to noise; hence a filter (like median filter, mean filter, morphological operations such as erosion and dilation) is needed to eliminate the noise from the image to be analyzed. Also a histogram equalization may be used to make the images at

comparable gray levels (as they came from different scanners), also to enhance the image contrast.

III. Methodology

A. Mammogram database.

The data collection that was used in our experiments was taken from the digital data base for screening mammography (South Florida University) it contain 2620, four view, mammography screening exams. (DDSM) [15]. The dataset consists of digitized mammogram images, composed of both oblique and cranio-caudal views. Each mammogram shows one (or more) clusters of microcalcifications marked by expert radiologists. The position of individual masses is marked. The location of each cluster of microcalcifications is given in the format of a contour surrounding the mass.

B. Extraction of ROI.

Using the contour supplied by the DDSM for each mammogram, we extracted the ROI of size 512 x 512 pixels with mass centered in the window. We have used 21 cases. These cases are digitized by the LUMISYS digitizer. They are cancerous cases. We got normal images from the cancerous images by taking regions away from the cancer region. From each image we took from one to three normal regions depending on the available normal space in the image. This resulted in 55 cancerous and 70 normal ROIs.

C. Feature extraction.

A typical mammogram contains a great amount of heterogeneous information that depicts different tissues, vessels, ducts, chest skin, breast edge, the film, and the X-ray machine characteristics. In order to build a robust CAD system that correctly classifies normal and abnormal regions of mammograms, we have to present all the available information that exists in mammograms to the diagnostic system so that it can easily discriminate between the normal and the abnormal tissue. However, the use of all the heterogeneous information, results to high dimensioned feature vectors that degrade the diagnostic accuracy of the utilized systems significantly as well as increase their computational complexity and calculation time. Therefore, reliable feature vectors should be considered that reduce the amount of irrelevant information thus producing robust Mammographic descriptors of compact size. In our approach, we examined a set of 35 features were applied to the ROI using a window of size 64x64 pixels with 64 pixels shift, (i.e. no overlap). The features used are:

1- Mean [16].
2- Standard deviation [16].
3- Variance [16].
4- Spreadness [17].
5- Entropy [16].
6- Range: It is the difference between the maximum and the minimum of a sample. The range is an easily-calculated estimate of the spread of the values in a data set.
7- Interquartile range (IQR): It is the difference between the 75th and the 25th percentiles of the values in a data set. The IQR is a robust estimate of the spread of the data, since changes in the upper and lower 25% of the data do not affect it. If there are outliers in the data, then the IQR is more representative than the standard deviation as an estimate of the spread of the data.
8- Mean absolute deviation (MAD): Also called average absolute deviation (AAD).
9- Invariant moments: It is the set of moments that are invariant to translation, rotation, and scale change (seven invariant moments) [18].
10- Percentile and Cumulative Frequency [19].
11- Skewness [16], [19].
12- Kurtosis [16], [19].
13- Fractal Texture Description: [20] We calculated the fractal dimension with eight fractal coefficients as fractal texture features.

D. Feature selection.

After the extraction of the previously mentioned features, it is found that not all the features can differentiate between normal and abnormal tissues. We applied a hypothesis test to decide whether the feature can discriminate or not.

We used the statistical hypothesis t-test. It performs a test of the hypothesis that the data in the vector of data set comes from a distribution with mean zero, and returns the result of the test. If the result equal zero it indicates that the null hypothesis (mean is zero) cannot be rejected at the 5% significance level. If the result equal one it indicates that the null hypothesis can be rejected at the 5% level.

E. Classifier.

The classification process is divided into the training phase and the testing phase. In the training phase, known data are given and the features are calculated by the processing which precedes classification. Separately, the data on a candidate region which has already been decided as a tumor or as normal are given, and the classifier is trained. We used the training set for this phase which consists of 35 cancerous ROI and 40 normal ROI. In the testing phase, unknown data are given and the classification is performed using the classifier after training. Breast cancer image diagnosis assistance is the task in the recognition phase. We used a testing set for this phase which consisted of 20 cancerous ROI and 30 normal ROI.

There are different types of classifiers. We used the minimum distance and the Voting K-Nearest Neighbor (K-NN) classifiers for their simplicity.

IV. Results Discussion

A. Features Extraction and selection.

First and without any enhancement we applied the previously mentioned 35 features using a window size of 64x64 pixels and a window shift of 64 pixels. Features are tested using a hypothesis test to decide whether or not this

TABLE I
SUMMARY OF RESULTS

		Minimum distance classifier		Voting K-Nearest Neighbor (K-NN) classifier			
				K = 1		K = 3	
		Train	Test	Train	Test	Train	Test
A	Sensitivity	80%	75%	100%	50%	91.4%	40%
	specificity	72.5%	70%	100%	73.3%	87.5%	76.7%
B	Sensitivity	80%	80%	100%	90%	94.3%	90%
	specificity	75%	63.3%	85%	76.7%	70%	70%
C	Sensitivity	91.4%	85%	100%	100%	100%	100%
	specificity	85%	80%	100%	90%	95%	90%

feature can discriminate between normal and abnormal tissues using a significance level of 5%. The test indicated that only 26 features can discriminate between the two clusters (spreadness, range, skewness, kurtosis, 5^{th} and 6^{th} invariant moments, 2^{nd} and 5^{th} and 7^{th} fractal coefficients are excluded).

Then we tried to enhance the images using the median filter and histogram equalization, and then the 35 features are applied and tested. In this case the test indicated that 31 features can be used to discriminate between the two clusters (range, skewness, 5^{th} and 6^{th} invariant moments are excluded).

B. Classifiers.

Results differed by applying different type of classifiers due to the fact that each classifier has its own method for the formulation of the normal and cancerous clusters upon which it decides whether a test ROI is considered cancerous or normal.

We measured, quantitatively, the detection performance of the classifiers by computing the sensitivity and specificity on the data. The sensitivity is the conditional probability of detecting a disease while there is in fact a cancerous breast. The specificity is the conditional probability of detecting a normal breast while the breast is indeed normal.

In the terms of the false-negative rate and the false positive rate:

$$\text{Sensitivity} = 1 - \text{false-negative rate} \quad (5)$$

$$\text{Specificity} = 1 - \text{false-positive rate} \quad (6)$$

False-negative rate: the probability that the classification result indicates a normal breast while the true diagnosis is indeed a breast disease (i.e. positive). This case should be completely avoided since it represents a danger to the patient.

False-positive rate: the probability that the classification result indicates a breast disease while the true diagnosis is indeed a normal breast (i.e. negative). This case can be tolerated, but should be as infrequent as possible.

So, the most important factor in judging the performance of any classifier is the sensitivity parameter. This parameter should be high as possible as we can. This parameter means the ability of detecting cancerous cases. If the case is cancerous and the system failed in detecting it, this will be a life threatening matter. But if the case is normal and the system classified it as cancerous, this error will be fixed by any further investigation like biopsy sample.

Each classification method was adopted to verify the classification results. The images are divided into the training set and the test set. The training set is used to build the classifier model and the test set is used to verify the trained classifier model. Note that the cases in the test set are not used to train the classifier model. Table (I) illustrates the results obtained using each of these classifiers in the three cases. Case (A) is obtained without enhancement and without the fractal features, case (B) is obtained without enhancement but with fractal features, and case (C) is obtained with fractal features after preprocessing to enhance the images.

Evaluating the results obtained, it's found that the best results obtained for both the training set and testing set is obtained when using K-NN classifier especially with K=1 and when using fractal features and enhanced images.

V. CONCLUSION & FUTURE WORK

In this study, a computer-aided diagnosis system for mammographic images based on statistical features, invariant features and fractal analysis is proposed. The input image is the ROI subimage containing the lesion pre-selected by a physician. The fractal analysis is applied to obtain the fractal texture features in order to classifying the test cases into normal and cancerous. From the experimental results, we can conclude the fractal analysis is useful to represent the texture information of breast lesions.

For further researches, fractal analysis and other texture features could be used for improving the classification performances. More cases must be added to the training set and to the testing set to cover the whole cluster space to obtain better results. Also, more advanced nonlinear classification methods such as neural network or fuzzy logic can be used to improve the classification accuracy. Also, the ROI is selected now by a physician. We need to develop an automatic tumor detection method to find the tumor location. If the system can automatically select the ROI, then the whole system can be applied for the breast screening. The segmentation method could be added in to the proposed system to find the tumor contour and only the texture information inside the tumor is used to diagnosis the tumor.

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