MICROCALCIFICATIONS ENHANCEMENT IN DIGITAL MAMMOGRAMS USING FRACTAL MODELING

Wael A. Mohamed[1], Mohamed A. Alolfe [2], and Yasser M. Kadah[2]
[1] Department of Electrical Engineering, High Institute of Technology, Benha University, Benha, Egypt
[2]System & Biomedical Engineering Department, Cairo University, Giza, Egypt
e-mail: waelbhit@k-space.org

Abstract- **Mammogram – breast x-ray imaging – is considered the most effective, low cost, and reliable method in early detection of breast cancer. Clustered Microcalcifications are an important early sign of breast cancer. In this paper, we are introducing, as an aid to radiologists, a computer-aided diagnosis (CAD) system, which could be helpful in detecting microcalcifications 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 fractal modeling of locally processed image (ROI). Classification between normal and microcalcification is done using the voting K-Nearest Neighbor classifier and the support vector machine classifier. The two classification techniques used were compared through the system to reach a better classification decision.**

***Keywords* - CAD, Mammography, Feature extraction, Microcalcification, Fractals, Classifier, Support Vector Machine (SVM).**

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 [1]. 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 – breast x-ray imaging – is the most effective, low cost, and reliable method that is used in the early detection of breast cancer [1], [2].

Microcalcifications are considered to be important signs of breast cancer. It has been reported that 30–50% of breast cancers detected radiographically demonstrate microcalcifications on mammograms, and 60–80% of breast carcinomas reveal microcalcifications upon histologic examinations. The high correlation between the presence of microcalcifications and the presence of breast cancers indicates that accurate detection of microcalcifications will improve the efficacy of mammography as a diagnostic procedure. The task of detection of microcalcifications for the diagnosis of breast cancer is a difficult one. Dense breasts, improper technical factors, or simple oversight by radiologists may contribute to the failure of detecting microcalcifications.

Given a mammogram, there are three major problems in analyzing and detecting microcalcifications.

1) Microcalcifications are very small. On mammograms, they appear as tiny objects which can be described as granular, linear, or irregular. According to the literature, the sizes of microcalcifications are from 0.1–1.0 mm, and the average diameter is about 0.3 mm. Small ones (ranging 0.1–0.2 mm) can hardly be seen on the mammogram due to their superimposition on the breast parenchymal textures and noise.
2) Microcalcifications often appear in an inhomogeneous background describing the structure of the breast tissue. Some parts of the background, such as dense tissue, may be brighter than the microcalcifications in the fatty part of the breast.
3) Some microcalcifications have low contrast to the background. In other words, the intensity and size of the microcalcifications can be very close to noise or the inhomogeneous background.

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].

Various numbers of techniques proposed to detect and classify the presence of abnormalities (masses and microcalcifications) in digital mammograms as benign or malignant. Karssemeijer [6] 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. [7] 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.

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.

Mascio *et al.* [8] developed an improved microcalcification detection algorithm, which combines morphological image processing with arithmetic processing on digital mammograms. The proposed system starts by applying two high-frequency analysis to the original image.

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The first analysis emphasizes any detail in the image that changes sharply in intensity and is larger than several pixels in size. The second analysis emphasizes any detail that is small and textured. Areas that are common to both analyses are segmented and kept for thresholding. This resulted in the detection of microcalcifications and suspicious areas.

Netch [9] proposed a detection scheme for the automatic detection of clustered MCCs using multiscale analysis based on the Laplacian-of-Gaussian filter and a mathematical model describing a microcalcification as a bright spot of certain size and contrast. D. Sankar, T. Thomas. [10] proposed a method for modeling the breast background tissues using mean and variance approach in the deterministic fractal model. in their study the average correlation between the original and the modeled mammograms were obtained as 0.9740 and the average mean square error was found to be 5.939. The results show that the true positive rate is 82% with an average of 0.214 negative clusters per image for 28 mammograms were obtained.

Li *et al.* [11] proposed using fractal background modeling, taking the difference between the original and the modeled image, which results in enhanced MCCs detection. Zheng *et al.* [12] proposed a method for the detection of microcalcifications clusters in digitized mammograms using mixed feature-based neural networks. Woods *et al.* [13] used a modified *k*-nearest neighbor (KNN) algorithm. The KNN rule used was more sensitive to microcalcification detection and less sensitive to non-microcalcifications. Cheng *et al.* [14] proposed a fuzzy logic approach for the detection of microcalcifications.

In the following parts, we will give a theoretical background of the fractal modeling in Section II. Section III provides information about our algorithm implementation and the proposed system. Results and discussion is achieved in Section IV. Conclusions are drawn in Section V.

II. Theoretical Background

Given a complete metric space (X, *d),* we can define the metric space (H(X), *h),* where H(X) is the space of compact subsets of X, and the distance $h : H(X) \times H(X) \rightarrow R$ between two sets *A* and *B* is the Hausdorff distance, which is characterized in terms of the metric *d.* Under these conditions, it can be shown that the metric space H(X) is complete according to the Hausdorff metric [15]. Let $f \in H(X)$ be an original image to be modeled. We wish to find contractive affine map τ: $H(X) \rightarrow H(X)$, satisfying the requirement

$$\forall f_1, f_2 \in H(X),\ h(\tau(f_1), \tau(f_2)) \le s \cdot h(f_1, f_2), \qquad (1)$$

and such that

$$h(f, \tau(f)) < \delta, \qquad (2)$$

where $s < 1$ and δ is a tolerance which can be set to different values according to different applications. The scalar *s* is called the contractivity of τ. τ can be a set of contractive mappings τ_i, i.e., $\tau = U_{i=1}^{N} \tau_i$. According to the deterministic fractal theory, a set of contractive mappings τ_i is the main part of an iterated function system *(IFS).* The definition of *IFS* is given as follows [15].

Definition 1: *An iterated function system (IFS) consists of a complete metric space* (*X*, *d) with a finite set* of *contraction mappings* $\tau_i : X \rightarrow X$, *with respective contractivity factors* s_i, *for* $i = 1,2, \ldots, N$, *and its contractivity factor is* $s = \max\{si : i = 1,2, \ldots, N\}$.

With the definition of *IFS,* one can state the important property of *IFS* in the following theorem.

Theorem 1: (The Collage Theorem) *Let (X , d) be a complete metric space. Let* $L \in H(X)$ *be given, and let* $\varepsilon \ge 0$ *be given. Choose an IFS { X ;* τ_i *} with contractivity factor 0* $\le s < 1$, *so that*

$$h\left(L, U_{n=0}^{N} \tau_n (L)\right) \le \varepsilon \qquad (3)$$

Then $h(L, A) \le \varepsilon / (1 - s)$, *for all* $L \in H(X)$, *where A is the attractor of the IFS.*[11]

The proof of the Collage Theorem can be found in [15]. The Collage Theorem shows that, once an *IFS* is found, i.e., τ is known such that $h(f, \tau(f)) < \delta$ is satisfied, then from any given image f_0 and any positive integer *n,* one can get

$$h\left(f, \tau^{on}(f_o)\right) \le \frac{1}{1-s} h\left(f, \tau(f)\right) + s^n h(f, f_o) \qquad (4)$$

Since $s < 1$, we see that after a number of iterations, the constructed image $f_n = \tau^{on}(f_o)$ will be close visually to the original image *f.*

The key point of fractal modeling is to explore the self-similarity property of images. Real world images are seldom self-similar, so it is impossible to find a transformation τ for an entire image. But almost all real images have a local self-similarity. We can divide the image into *n* small blocks, and for each block find a corresponding τ_i. So finally, we can define $\tau = U_{i=1}^{N} \tau_i$

III. Algorithm Implementation

Now we introduce a mathematical representation for digital gray-level images Let $N_1 = [0,1, \ldots, M]$, $N_2 = [0,1, \ldots, N]$, $N_3 = [0, 1 \ldots L]$, respectively, then for any digital gray-level image $f(k,l)$, we have $(k,l,f(k,l)) \in N_1 \times N_2 \times N_3$. Let $D_1, \ldots D_n$ and $R_1, \ldots, R_n$ be subsets of $N_1 \times N_2$, such that $U_{i=1}^{n} R_i = N_1 \times N_2$ and $R_i \cap R_j = \phi$, $i \neq j$. We call R_i the range squares, and D_i the domain squares. τ_i can be defined as

$$\tau_i(f(k,l) = s_i \overline{f}(k,l)|_{(k,l)\epsilon D_i} + o_i \qquad (5)$$

Where s_i is a scaling factor and o_i is an offset factor. The error may be written as:

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$$e_i = \sum_k \sum_l (f(k,l) - (s_i \overline{f}(k,l) + o_i))^2 \quad (6)$$

The main target in our system is: for each R_i, a $D_i \subset N_1$ x N_2 and $\tau_i : N_1$ x N_2 x $N_3 \rightarrow N_3$ are sought such that the error is minimized. A value is set for the uniform tolerance $\delta_i = \delta$', and the best D_i is selected such that $e_i < \delta$'.

Suppose there is microcalcifications (clusters or some single isolated ones) on the image block above R_i, our intention is to find an area D_i on which the image has a similar structure as on R_i but does not have similar microcalcification patterns. Then when a difference between the original image and modeled image is taken, the microcalcifications will be enhanced. This means that when searching for D_i, the suitable D_i should not cover the region of R_i. In the proposed algorithm, for each given R_i, we constrain the search way of D_i by $R_i \cap D_i = \phi$.

A. Fractal Modeling:

The fractal modeling may be done via the following steps.

1) Choose R_i so that they are a non-overlapping blocks of size 8x8.
2) Perform a search for D_i that satisfy $R_i \cap D_i = \phi$, and $e_i < \delta$' condition is satisfied. If this condition is not satisfied, the domain with minimum error is selected.
3) The process is continued until the whole image is modeled.
4) Based on the Collage Theorem, the modeled image can be obtained easily by iteration according to τ_i and D_i. The iteration stops when the predetermined tolerance between the original and the modeled image is achieved.

B. MCCs enhancement:

Microcalcifications may be enhanced by using the fractal modeling in the following manner. Let the original and the modeled images be *f(k,l)* and *g(k,l)* respectively. The enhanced image (from which background structures were removed) may be achieved by subtracting the two images and ignoring the negative values which does not contain any information about spots brighter than background (microcalcifications). It may be written as,

$$f_1(k,l) = max(0, [f(k,l) - g(k,l)]), \quad (k,l) \in N_1 \text{ x } N_2 \quad (7)$$

C. MIAS database:

Due to privacy issues, real medical images are difficult to access for experimentation. The data used in our experiments was taken from the Mammographic Image Analysis Society (MIAS) [16]. This database consists of 322 images divided into normal and abnormal (benign and malignant). The abnormal cases are divided into six groups: circumscribed masses, spiculated masses, microcalcifications, ill-defined masses, architectural distortion and asymmetry. The existing data in the collection consists of the location of the abnormality (like the center of a circle surrounding the tumor, its radius), breast position (left or right), type of breast tissues (fatty, fatty-glandular and dense) and also the tumor type if exists (benign or malign).

D. ROI Selection:

Taking the guidance from the locations of abnormalities (microcalcifications) supplied by the MIAS, the ROI of size 64×64 pixels was extracted with MCCs centered in the sub-image. The ROIs are divided into training and testing sets. The training set composed of 50 normal and 13 abnormal and the testing set contains 50 normal and 12 abnormal.

E. features Extraction

Features are extracted from the original and the enhanced ROIs. We computed the contrast, the peak signal to noise ratio, and the average signal to noise ratio. The contrast C is defined by:

$$C = \frac{f-b}{f+b} \quad (8)$$

Where *f* is the mean gray-level value of a particular object in the image, called the foreground, and *b* is the mean gray-level value of a surrounding region called background.

The peak and average signal to noise ratio *(PSNR) & (ASNR)* are defined as:

$$PSNR = \frac{p-b}{\sigma} \quad (9)$$

$$ASNR = \frac{f-b}{\sigma} \quad (10)$$

Where p is the maximum gray-level value of a foreground. And σ is the standard derivation in the background region.

F. Classification

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. 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.

There are different types of classifiers. We used the voting K-Nearest Neighbor (K-NN) classifier and the Support Vector Machine (SVM) classifier to classify between normal and abnormal cases.

F1. K-NN classifier

The k-NN classification is nonparametric technique, i.e., it assigns a test sample to the class of the majority of its K-neighbors. In other words, that is, assuming that the number of voting neighbors is $k=k_1+k_2+k_3+...+k_i$ (where k_i is the number of samples from class i in the k-sample neighborhood of the test sample), the test sample is assigned to class m if $k_m = \max \{k_i, i=1, 2, 3\}$ [48]. Through this study, we compared the results of using k=1, k=3, and k=5.

F2. Support Vector Machine (SVM) classifier

SVM has the potential to handle very large feature spaces, because the training of SVM is carried out so that the dimension of classified vectors does not has as distinct an

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TABLE I
SUMMARY OF RESULTS

		SVM		K-NN					
				K=1		K=3		K=5	
		Train	Test	Train	Test	Train	Test	Train	Test
Original Image	Sensitivity	100%	100%	100%	58.3%	92.31%	66.67%	92.31%	41.67%
	Specificity	90%	80%	90%	70%	80%	70%	80%	70%
Enhanced Image	Sensitivity	100%	100%	100%	91.67%	92.31%	91.67%	92.31%	91.67%
	Specificity	100%	96%	90%	70%	80%	76%	70%	70%

influence on the performance of SVM as it has on the performance of conventional classifier. That is why it is noticed to be especially efficient in large classification problem. This will also benefit in faults classification, because the number of features to be the basis of fault diagnosis may not have to be limited. Also, SVM-based classifier is claimed to have good generalization properties compared to conventional classifiers, because in training SVM classifier the so-called structural misclassification risk is to be minimized, whereas traditional classifiers are usually trained so that the empirical risk is minimized.

IV. RESULTS & DISCUSSIONS

All results from the proposed system are shown in table (I) where we repeated all the work for both the original and the enhanced images. Two types of classifiers are used to classify the images into normal or cancerous.

It is clear from the table that we measured, quantitatively, the detection performance of the each classifier 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:

$$\text{Sensitivity} = 1 - \text{false-negative rate} \quad (11)$$
$$\text{Specificity} = 1 - \text{false-positive rate} \quad (12)$$

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 testing set. The training set is used to build the classifier model and the testing set is used to verify the trained classifier model.

Evaluating the results obtained, it's found that the best results obtained when using SVM classifier and the fractal modeling to enhance the microcalcifications in the digital mammograms.

V. CONCLUSION

In this study, a computer-aided diagnosis system based on fractal modeling for microcalcification enhancement is proposed. This system depends on mammographic microcalcification enhancement using the Collage Theorem for fractal modeling.

All results obtained in this study are very encouraging, and indicate that the fractal modeling is an effective technique to extract mammographic patterns and to enhance microcalcifications embedded in inhomogeneous breast tissues. Therefore, the proposed method may facilitate the radiologists' diagnosis of breast cancer.

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