Fast Fractal Modeling of Mammograms for Microcalcifications Detection

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Abstract

Clusters of microcalcifications in mammograms are an important early sign of breast cancer in women. Comparing with microcalcifications, the breast background tissues have high local self-similarity, which is the basic property of fractal objects. A fast fractal modeling method of mammograms for detecting the presence of microcalcifications is proposed in this paper. The conventional fractal modeling method consumes too much computation time. In the proposed method, the image is divided into shade (homogeneous) and non-shade blocks based on the dynamic range and only the non-shade blocks are modeled. Reducing the number of the processed blocks reduces the encoding time to 6.372% compared to the conventional modeling method. The modeled mammograms were investigated for microcalcifications detection and the results show that the sensitivity is 92% for 25 abnormal mammograms were obtained.

1. 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 – 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.

- ☑ 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.
- ☑ 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.
- ☑ 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.

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 techniques proposed to detect the presence of microcalcifications in digital mammograms as a sign of cancer presence. 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. 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 Microcalcifications 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.

In the following parts, we will give a theoretical background of the fractal modeling in Section 2. Section 3 provides information about our algorithm implementation and the proposed system. Results and discussion is achieved in Section 4. Conclusions are drawn in Section 5.

2. 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 [12]. Let $f \in H(X)$ be an original image to be modeled. We wish to find contractive affine map $\tau: H(X) \rightarrow H(X)$, satisfying the requirement

$$\forall f_1, f_2 \in H(X),\ h(\tau(f_1),\ \tau(f_2)) \leq s \cdot h(f_1, f_2), \tag{1}$$

and such that

$$h(f,\ \tau(f)) < \delta, \tag{2}$$

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., $\tau = \mathbf{U}_{i=1}^{N} \tau_i$. 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 [12].

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 $s = max\{s_i : i = 1,2, \ldots, N\}$.

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 $\varepsilon \geq 0$ be given. Choose an IFS $\{X; \tau_i\}$ with contractivity factor $0 \leq s < 1$, so that

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

Then $h(L, A) \leq \varepsilon / (1- s)$, 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 [12]. 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

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

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 $\tau = U_{i=1}^{N} \tau_i$

3. Algorithm Implementation

Jacquin had classified the image into shade, midrange and edge blocks [13, 14] but D. Sankar and T. Thomas said that the image blocks may be classified into shade and non shade blocks based on their visual perception [15]. In this paper we used D. Sankar and T. Thomas method and only the non shade blocks are modeled using the fractal modeling method. Thus, the computation time required in the fractal modeling procedure can be considerably reduced.

The image of square size 64x64 is divided into non overlapping range blocks of size 8x8. These range blocks are then classified into shade and non shade blocks. Shade blocks are those blocks that has no major gradients or texture and the gray scale of pixels change slowly or little to human eyes perception. A non shade block has some sudden changes in pixel intensities looking like texture or distinct edges which can be perceived. To classify these blocks the dynamic range (ratio between max. and min. pixel values) of the block is calculated. The block is classified as shade block if the dynamic range is less than 0.05 else it is a non shade block and it has to be modeled by the following procedure.

Here, a mathematical representation for digital gray-level images is introduced. 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

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

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

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

The main target in our system is: for each R_i, a $D_i \subset N_1 \times N_2$ and $\tau_i : N_1 \times N_2 \times N_3 \rightarrow N_3$ 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 $e_i < \delta'$.

Since we are processing only the non shade blocks, we consider that 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 $R_i \cap D_i = \phi$.

3.1. Fractal Modeling:

The fractal modeling may be done via the following steps.

1) Choose R_i so that they are a non-overlapping subsquares 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.

3.2. Microcalcifications 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,

$$f_1(k,l) = max(0, [f(k,l) - g(k,l)]), \qquad (k,l) \in N_1 \times N_2 \tag{7}$$

3.3. 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).

3.4. 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 Microcalcifications centered in the sub-image. The ROIs selected were 100 normal and 25 abnormal images.

3.5. 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:

$$C = \frac{f-b}{f+b} \tag{8}$$

Table I, *Summery of results*

Method	Mammograms	Samples	Sensitivity	Specificity	Average time in minutes
Conventional	Normal	100	-	94%	24.3501
	Abnormal	25	92%	-	23.0833
Proposed	Normal	100	-	97%	0.8167
	Abnormal	25	92%	-	2.2057

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

3.6. Classification

There are different types of classifiers. Through this study, we used Support Vector Machine (SVM) classifier to classify between normal and abnormal cases. 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 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.

4. Results & Discussions

All results from the proposed system are shown in table (I) where we repeated all the work using both the conventional fractal modeling and our proposed system. The encoding time for the conventional method of fractal coding was 23.7167 minutes in average, while the proposed method took only 1.5112 minutes when encoding normal and abnormal mammograms. Thus a saving of 93.628% of the encoding time is obtained using the proposed fractal modeling method.

It is clear from the table that we measured, quantitatively, the detection performance of the classifiers by computing the sensitivity and specificity on the data 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.

5. Conclusion

In this study, a proposed system for fast fractal modeling of mammograms for microcalcifications detection is presented. The selected ROI is divided into non overlapping range blocks, these blocks are then classified into shade and non shade blocks according to their dynamic range. This system depends on mammographic microcalcification enhancement using the Collage Theorem for fractal modeling of only the non shade blocks.

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

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