ENHANCEMENT OF MICROCALCIFICATIONS ON MAMMOGRAMS USING A FRACTAL MODELING APPROACH

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Abstract— The objective of this research is to model the mammographic parenchymal, ductal patterns and enhance microcalcifications using a fractal approach. According to the theory of deterministic fractal geometry, images can be modeled by deterministic fractal objects which are attractors of sets of two dimensional affine transformations. In this paper, a methodology based on fractal image modeling is developed to analyze and extract various mammographic textures. We show that general mammographic parenchymal and ductal patterns can be well modeled by the proposed approach. Therefore, microcalcifications can be enhanced by taking the difference between the original mammogram and modeled mammogram. Our results are compared with those of the partial wavelet reconstruction and morphological operation approaches. The results demonstrate that the fractal modeling method is an effective way to enhance microcalcifications, and thereby facilitate the radiologists' diagnosis. It is also able to improve the detection and classification of microcalcifications in a computer system.

I. INTRODUCTION

The abnormal mammogram is usually composed of the normal breast tissues (mammographic parenchymal, ductal patterns), the disease patterns(masses, microcalcifications), and the film defects (noises). Microcalcifications are one of the disease patterns. They are early signs of breast cancer. In mammogram, Microcalcifications are visible as small bright spots and have less structure. Some microcalcifications are very subtle and are easy to be missed by radiologists [1]. On the other hand, the breast tissues possess structures with high self-similarity. If the tissue patterns can be modeled and be taken out from the original image, the microcalcification information will be enhenced. It is very helpful for doctors to detect the microcalcifications.

Recently, fractal-based techniques have been applied in many areas of images processing, such as image segmentation, image analysis [2], [3]. In fractal theory, images could be modeled by deterministic fractal objects which are attractors of sets of two-dimensional affine transformations. We use this approach to model breast tissue structures and enhance microcalcifications by taking the difference between the original mammogram and modeled image. The results are very encouraging.

II. METHODS

The mathematical theories of Iterated Function Systems and the Collage Theorem are the foundations of fractal image modeling [4]. Let (M, d) denote a metric space of digital images, where d is a given distortion measure, and let f be an original image which to be modeled. We want to find a contractive mapping τ such that: $d(f, \tau(f)) < \delta$ where δ is a tolerance. The Collage Theorem shows that, if τ is known, then from any given image f_0, after a number of iterations, the constructed image $f_n = \tau^n(f_0)$ will close visually to original image f. The key point of fractal modeling is to explore the self-similar property of images. Real world images are almost never self-similar, but almost all real images have a local self similarity. The image can be divided into n small blocks, and for each block, find a corresponding τ_i. Then, we can define $\tau = \cup_{i=1}^n \tau_i$. Let $N_1 = [0, 1, ..., M], N_2 = [0, 1, ..., N], N_3 = [0, 1, ..., L]$, then for any digital gray-level image $f(x, y)$, we have $(k, l, f(k, l)) \in N_1 \times N_2 \times N_3$. Let $D_1, ..., D_n$ and $R_1, ..., R_n$ be subsets of $N_1 \times N_2$, such that $\cup_{i=1}^n R_i = N_1 \times N_2$ and $R_i \cap R_j = \phi, i \neq j$. We define a set of mixing functions $m_i : N_1 \times N_2 \to N_1 \times N_2$, such that $m_i(R_i) = D_i$ using a affine mapping. τ_i can be defined as: $\tau_i(f(k, l)) = s_i f(m_i(k, l)) + o_i$, where s_i is a scaling factor and o_i is an offset factor. Also, let us denote $f|_{R_i}$ be the restriction of the function f to the set R_i. In practice, we use $d(\cdot, \cdot)$ as the mean square root metric and $f(m_i(k, l)) = \bar{f}(k, l)$, where

$$\bar{f}(k, l) = \frac{\sum_{i=0}^1 \sum_{j=0}^1 f(k + i, l + j)}{4}. \tag{1}$$

The goal is for each R_i, a $D_i \subset N_1 \times N_2$ where a constraint $R_i \cap D_i = \phi$ is given and $\tau_i : N_1 \times N_2 \times N_3 \to N_3$ are sought such that

$$\|f(k, l)|_{(k,l) \in R_i} - (s_i \bar{f}(k, l)|_{(k,l) \in D_i} + o_i)\|_2^2 \tag{2}$$

is minimized. Once all τ_i are found, the modeled image can be got by the iterations from any starting image of the same size according to D_i and τ_i. The microcalcifications can be enhanced by taking the difference between the original mammogram and modeled mammogram.

III. RESULTS

Ten real mammograms with clustered and single microcalcifications were chosen as testing images. The areas of

suspicious microcalcifications were identified by a highly experienced radiologist. The selected mammograms were digitized with an image resolution of $100\mu m \times 100\mu m$ per pixel by the Lumisys DIS-1000. All images are $512 \times 512 \times 12$ bpp. We found that the general mammographic parenchymal and ductal patterns could be well modeled and most microcalcifications were enhanced successfully. Fig. 1 shows the modeled and enhanced results of one of the real mammograms. As we can see in Fig. 1 (b), the general mammographic parenchymal and ductal patterns in mammograms were well modeled. In Fig. 1 (c), we can see that all less-structured spots, which include clusters of microcalcifications, single microcalcifications, and film detects, were clearly enhanced.

For the purpose of evaluating the performance of our proposed fractal enhancement method, we chose for comparison two similar enhancement techniques of background removal: the morphological and partial wavelet reconstruction methods [5], [6]. A global thresholding was applied to reduce unreliable noise in the fractal, morphological and wavelet approaches. Fig. 2 shows the enhancement results of clustered and single microcalcifications in the mammograms. The first, second, third, and fourth rows in Fig. 2 correspond to original ROIs, fractal enhancement, wavelet enhancement, and morphological enhancement, respectively.

IV. DISCUSSION

The size of R_i and the value of δ can affect the modeling process. Large block size would result in visible artificial edge effects on the modeled image, which are not good for segmenting the microcalcifications. On the other hand, the small R_i would have less structure information which causes it to be difficult to search for correct D_i. A similar situation occurs when we choose δ. Large δ would introduce more noise and wrong structure on the modeled image. But small δ would result in no solution of the search process. In our experiment, we found that the suitable block size of R_i is from 32×32 to 8×8, and the range of δ is $10.0 \sim 20.0$.

The results in Fig. 2 indicated that all three approaches removed the background, and in turn enhanced less structured spots, including microcalcifications. We noted that even for the spots embedded in the bright background (such as dense tissues), the enhancement results were still very promising. Furthermore, we observed that the fractal and morphological approaches can remove more background structures than the wavelet approach does, especially for those ROIs with very low contrast compared with the surrounding background. But the wavelet approach can preserve the overall shape of spots better than the other two approaches.

In order to quantitatively measure the enhancement performance with different approaches, we computed the contrast, the noise level, the peak signal to noise ratio. Among these three approaches, the noise level of the fractal approach was the lowest. The contrast and the peak signal to noise ratio of the fractal approach were better than those

of the wavelet and morphological approaches. All results obtained in this study are very encouraging, and indicate that the fractal modeling and segmentation method is an effective technique to enhance microcalcifications embedded in inhomogeneous breast tissues.

V. CONCLUSIONS

In this research, we proposed a microcalcification enhancement algorithm based on the fractal modeling scheme. We compared the enhancement results with those based on morphological operations and partial wavelet reconstruction methods. The results indicated that the proposed method can facilitate the radiologists' diagnosis of breast cancer. We expect that the proposed fractal method can also be used for improving the detection and classification of microcalcifications in a computer system.

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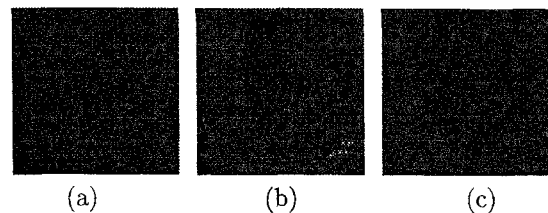
(a) (b) (c)

Fig. 1. The modeling and enhancement results of one real mammogram using the fractal modeling approach. (a) Original mammogram; (b) Modeled mammogram; (c) Enhanced result.
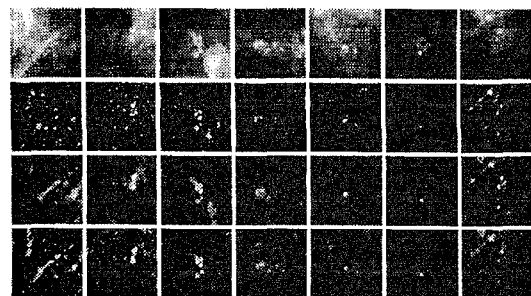

Fig. 2. The enhancement results of clustered microcalcifications on selected ROIs on mammogram using the fractal, wavelet, and morphological approaches.