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A Novel Approach to Computer-Aided Diagnosis of Mammographic Images

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Abstract--- **This is a work-in-progress report of a research endeavor that deals with the design and development of a novel approach to computer-aided diagnosis (CAD) of mammographic images. With the initial emphasis being on the analysis of microcalcifications, the proposed approach defines a synergistic paradigm that utilizes new methodologies together with previously developed techniques. The new paradigm is intended to promote a higher degree of accuracy in CAD of mammograms with an increased overall throughput. The process of accomplishing these goals is initiated by the fractal encoding of the input image, which gives rise to the generation of *focus-of-attention regions* (FARs), that is, regions that contain anomalies. The primary thrust of this work is to demonstrate that by considering FARs, rather than the entire input image, the performances of the ensuing processes (i.e., segmentation, feature extraction, and classification) are enhanced in terms of accuracy and speed.**

After presenting the proposed approach to CAD of mammographic images, the paper describes the generation of FARs. Furthermore, an experimental study is included that demonstrates the impact of this front-end procedure on the process of microcalcification segmentation. Specifically, the experimentation reveals a dramatic decrease (increase) in the amount of input data (throughput), as well as a reduction in the number of false detections.

I. Introduction

Breast cancer is a deadly disease that adversely affects the lives of far too many people, primarily women. According to the National Cancer Institute [1], each year about 180,000 women in the United States develop breast cancer, and about 48,000 lose their lives to this disease. It is also reported that a woman's lifetime risk of developing breast cancer is 1 in 8. Scientific studies conducted over a 30-year period, and involving nearly 500,000 women, clearly suggest that breast cancer screening tests performed on a regular basis play a crucial role in reducing the rate of mortality, especially among women ages 50 and older. The screening tests include mammography, clinical breast examination, breast self-examination, or a combination of the above. Of these tests, mammography has proven to be the most effective for the early detection of nonpalpable microcalcifications.

As periodic screening becomes routine, the number of mammograms to be diagnosed by radiologists will increase dramatically. It has been reported that the percentage of women over 40 years of age who had ever received at least one mammogram rose from 38% in 1987 to 60% in 1990 [1]. As a result, a focused effort, which was initiated two decades ago, is under way to develop CAD systems to aid the radiologists and to increase the overall consistency and throughput of the screening process.

In our work, we intend to take advantage of the previously developed work but to do so with a renewed emphasis on achieving a higher degree of accuracy while maintaining a high throughput. This is initiated by the application of a fractal-based, global image analysis scheme that preprocesses the input images to generate FARs for the ensuing segmentation techniques. FARs contain mammographic anomalies (i.e., microcalcifications, lesions, and other events) that are visually distinct from the normal structures. Although the idea of an initial reduction of the input data has been implemented before, for example in [2], until this work, it had not received its due consideration.

In the following sections, we begin by presenting our proposed approach to CAD of mammographic images and proceed by describing the generation of FARs and the impact of this action on the process of microcalcification segmentation.

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II. CAD OF MAMMOGRAPHIC IMAGES

There are three major steps in accomplishing any computer vision task, and CAD of mammographic images is no different. The design and execution of these steps, which include segmentation (i.e., detection and localization), feature extraction, and classification, are to result in the accurate characterization of mammographic abnormalities (i.e., microcalcifications and lesions). To this end, over 20 years of focused research has given rise to an impressive body of work that includes a variety of highly effective, yet distinct, algorithmic methodologies.

The proposed approach to CAD of mammographic images (Fig. 1) provides a framework within which the previously developed methodologies can be utilized synergistically. More importantly, the overall process complements the traditional three-step approach in the following ways:

- A fractal-based, front-end processor is employed that examines the input image globally and generates FARs as inputs to the ensuing local processors. This type of approach parallels the analysis performed by radiologists who seem to progress from general to detailed processing. The advantages of this approach are twofold: (1) reduction of data, which results in an increased throughput, and (2) reduction of false detections, which can ultimately give rise to a reduction in the number of false positives.
- In the segmentation step, each FAR is processed by multiple techniques. These techniques may represent distinct methods, different forms of the same method, or a combination of the above. Given the variability of abnormalities in mammograms, this strategy is expected to increase the accuracy of abnormality detection and localization. Furthermore, because of the reduction of data as a result of FAR generation, this overanalyzing of image subregions will not decrease the overall throughput.
- Classification is performed on the basis of features that are extracted from the surroundings of the abnormalities, as well as from the abnormalities themselves. This means that crucial information such as whether or not the segmented microcalcifications are clustered or the size and shape of these clusters can be incorporated into the classification process.

The described characteristics of the proposed CAD system are intended to increase the accuracy of abnormality segmentation and characterization without having a negative impact on the overall throughput. In the next section, we discuss the generation of FARs from the fractal encoding of the input images.

III. GLOBAL IMAGE ANALYSIS

As mentioned previously, global image analysis of the incoming digitized mammograms is to achieve a reduction in the amount of input data and in the number of false detections. To accomplish this, we propose the generation of FARs by employing the fractal encoding technique.

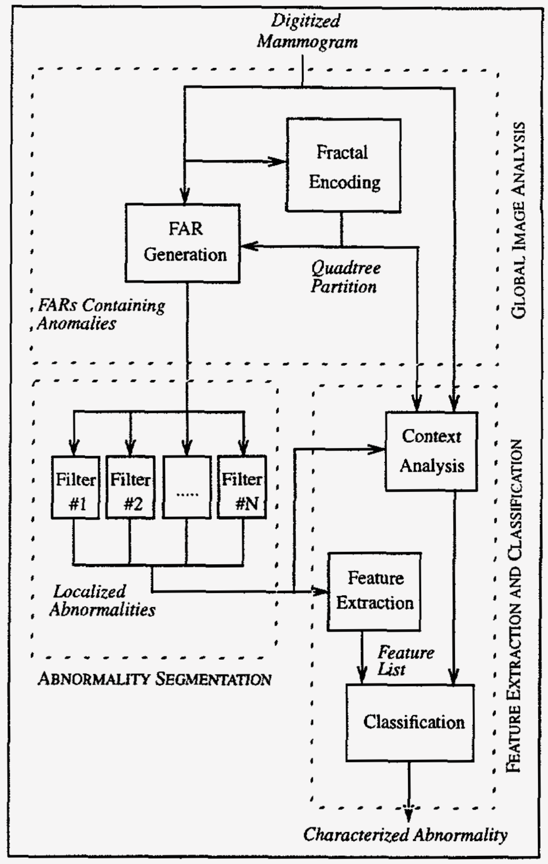
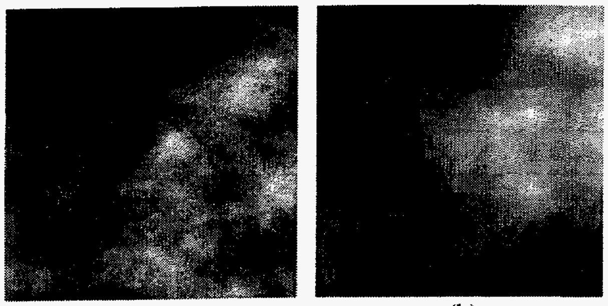


Fig. 1. Proposed approach to CAD of mammographic images.

A. Fractal Image Encoding

Fractal analysis of digitized images of mammograms has been pursued previously through the extraction of fractal features (e.g., fractal dimension). Using fractal encoding as a first step for abnormality segmentation and characterization has not been addressed and is proposed here as a unique feature of our CAD system. The primary motivation for pursuing a fractal-based representation is that localized inspection of mammographic images reveals their visual similarity to images of clouds, which have been the target of successful fractal modeling [3]; see Fig. 2.

Fractal image encoding is the first of two steps executed in fractal image compression; the second being decoding. The topic of fractal image compression has received considerable attention since the publication of the first practical scheme by Jacquin in [4]. In this paper, we present a rather superficial discussion of this topic that serves our



(a) (b)

Fig. 2. Similarity between the visual characteristics of a mammographic subimage in (a) and a synthetically generated fractal image in (b). The fractal image was generated using the midpoint displacement technique with a fractal dimension of 2.2.

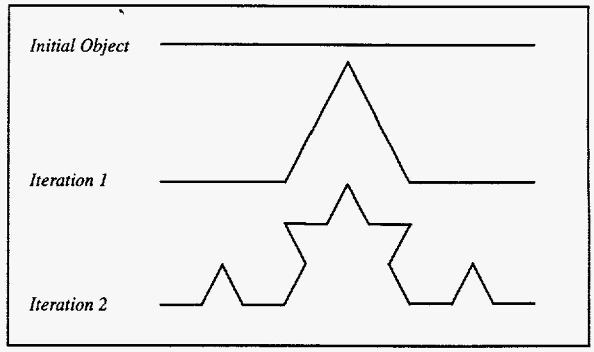


Fig. 3. Iterative generation of a self-similar fractal curve. In each iteration, the mapping consists of scaling by a factor of 1/3, rotation by ±45 degrees, and translation.

purposes. The interested reader is referred to [5] for a more detailed treatment of the subject matter.

Fractal compression, or more specifically, fractal encoding exploits the property of self-similarity of fractal objects. Exact self-similarity means that the fractal object is composed of scaled-down copies of itself that are translated, stretched, and rotated according to a prescribed mapping or transformation (Fig. 3). If the map is contractive (i.e., it always brings points closer together), then the Fixed-Point Theorem guarantees that the generated fractal object (attractor) is unique and independent of the choice of the initial object. Therefore, given that one is dealing with a simple transformation, compression is achieved when the coefficients of the map are stored in place of the attractor. An example of a commonly employed mapping is the affine transformation, A, of the following form:

$$A\begin{bmatrix}x\\y\\z\end{bmatrix} = \begin{bmatrix}a & b & 0\\c & d & 0\\0 & 0 & e\end{bmatrix}\begin{bmatrix}x\\y\\z\end{bmatrix} + \begin{bmatrix}e\\f\\o\end{bmatrix}.$$

This transformation is capable of generating a variety of attractors by translating, scaling, rotating, and adjusting the contrast and brightness of an input image. But, do real images exhibit exact self-similarity? In general, the answer is no; however, real images do exhibit *partitioned* self-similarity. That is to say that instead of being formed of copies of its *whole* self, the image is composed of properly transformed *parts* of itself [5].

In computing the coefficients of the affine transformation, the basic premise is that because of the notion of partitioned self-similarity, each subregion of the image can be described (in the sense of minimizing a dissimilarity metric) in terms of another. The former subregion belongs to the range pool, R, while the latter belongs to the domain pool, D, of the map. If a given subregion in R cannot be *covered* by any region in D (i.e., their measure of dissimilarity is above a specified threshold, T), then R is further partitioned into smaller subregions. This process continues recursively until either a similar subregion from D is found or a specified maximum level of partitioning, L_{max}, is reached. It is important to note that an exhaustive search to find matches between the subregions in the range and domain pools will in fact render this encoding scheme computationally paralyzed. Generally, the subregions are classified into a manageable number of classes, and searches for similar regions occur only between those candidates that belong to the same class. The classification, as well as the range pool partitioning procedures can take on a variety of forms [5]. Thus far in this work, we have chosen to employ Fisher's classification technique and the commonly utilized quadtree partitioning scheme [5].

B. Focus-of-Attention Region Generation

Our hypothesis is that for subregions in R that contain mammographic anomalies, either in part or in whole, L_{max} will be reached during the fractal encoding process. The reasoning is that the visual appearance of microcalcifications is almost always dissimilar to that of the coexisting normal structures. Therefore, subregions in D that can be used to cover those areas in the image with microcalcifications are expected to be nonexistent; see Figs. 4(a) and (b). A crucial issue that must be addressed is that of false negatives, that is, we must make sure that all anomalies are passed on to the ensuing segmentation procedure as FARs. To accomplish this, we simply choose the parameters of the encoding process quite conservatively. Furthermore, along with those subregions that are flagged as containing anomalies, we also include their neighbors; see Fig. 4(c). It should be noted that FARs that are indicated in Fig. 4(d) represent only 11% of the original data.

In the next section, an experimental study is included that reveals the extent by which both the input data and the false detections are reduced for a set of 39 images.

IV. Evaluation and Results

The front-end, global image analysis, as described in the

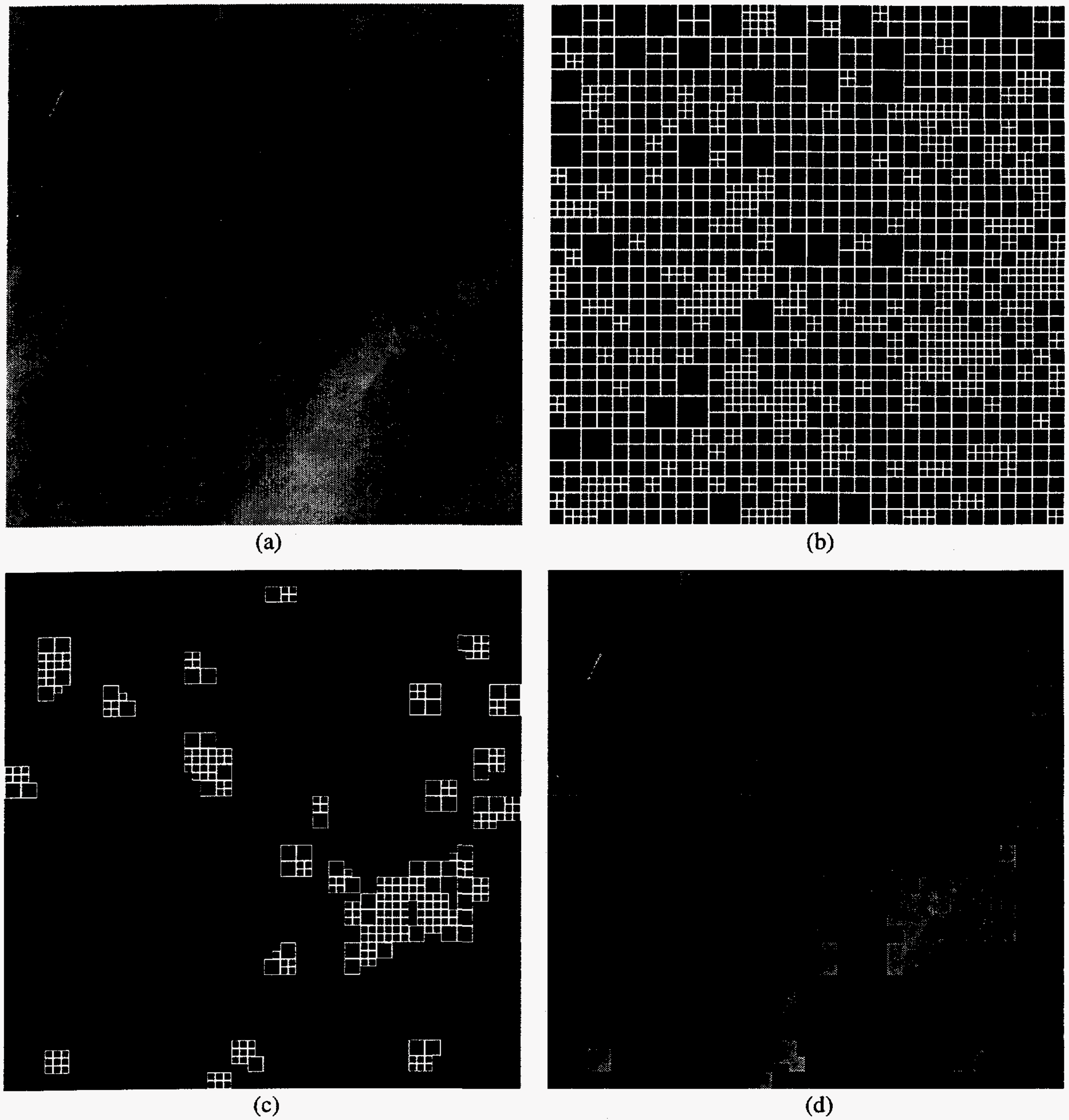


Fig. 4. (a) A mammographic image with clustered microcalcifications in the lower-right quadrant and other anomalies in the upper-left quadrant of the image. (b) Quadtree partitioning as a result of the fractal encoding of the image in (a) for $L_{max} = 6$ (smallest subimages are 8 x 8) and $T = 3.4$. (c) Those subregions, and their 8-neighbors, in (b) that never satisfied the similarity condition. (d) Generated FARs; note their concentration in the lower-right and the upper-left quadrants.

previous section, is a unique feature of the proposed CAD system that initiates an overall improvement in accuracy and throughput. Here, we discuss the impact of the fractal encoding scheme on the microcalcification segmentation process.

Of the segmentation techniques that have been earmarked for evaluation and inclusion in the proposed CAD system, one was implemented for the purpose of conducting this study. This technique, which is developed by Dengler et al. [6], is relatively simple to implement. It requires the specification of six parameters, all of which are well defined, and it achieves a remarkable true detection rate for microcalcifications. The segmentation process is a two-phase procedure, each of which operates on the input image independently and generates output images that are ultimately merged. The first phase is accomplished in two sequential steps. First, Gaussian-based, unsharp masking is employed to remove the effect of background intensity variations. Because of the observed polarity of microcalcifications, only the positive values are retained. In the second step, a weighted difference of Gaussian filter is applied to accomplish a noise-invariant, size-specific segmentation of microcalcifications. The second phase of the segmentation process consists of the morphological, top-hat transformation of the input image. The shapes of the microcalcifications detected in this manner are better preserved but at the cost of more false detection occurrences. To remedy this, the output images generated in each of the two phases are merged using a morphological, conditional thickening operation. In the merged output image, the detected objects have well-preserved shapes, and there are as many of them as the intersection of the outputs from the two phases.

For the experimental study, we selected 39, 512 x 512 mammographic images*, digitized at a resolution of 50 µm/pixel. Seventeen of these images contain marked microcalcifications [example in Fig. 5(a)], and twenty-two contain no microcalcifications [example in Fig. 6(a)]. It is important to include the latter set because, realistically, an overwhelming majority of mammograms that are analyzed by radiologists contain few or no abnormalities. The described segmentation technique, as well as the fractal encoding scheme, were applied to each of the above images. For the example images, the detected objects are marked with green and red overlays in Figs. 5(b) and 6(b). The generated FARs are also indicated in these images by the rectangular, highlighted areas.

The segmentation technique produced a total of 110 (minimum of 0 and maximum of 20) false detections in the images with microcalcifications and a total of 374 (minimum of 0 and maximum of 37) in images without. True and false detections are distinguished based on a visual evaluation of the images and their corresponding outputs. Utilizing this technique in conjunction with the proposed fractal encoding scheme would reduce the above numbers to 23 and 57, respectively. For each image, this reduction is quantified as false detections that are not contained by or touching any FARs; indicated by red overlays in Figs. 5(b) and 6(b). As important as the reduction in false detections is the reduction in the input data, which can ultimately impact system throughput. The generated FARs for our trial images represented a reduction of data by amounts ranging from 81% to 99%. It is important to mention that the parameter values for both the segmentation technique and the fractal encoding scheme were identical for all the test images.

For a more efficient and accurate segmentation, one scenario would be to employ multiple instances of the above segmentation technique within the proposed CAD system (Fig. 1). This would give rise to size invariance by allowing the specification of different parameter values for each instance of the filter without decreasing the overall throughput of the system.

* Subset of a database compiled by the Mammographic Image Analysis Society, United Kingdom.

V. Discussion

The overall objective as well as the preliminary results of a research endeavor dealing with CAD of mammographic images are presented. The proposed approach seeks to achieve a higher degree of accuracy in the characterization of mammographic abnormalities while maintaining a high throughput. This is accomplished in part by discarding portions of the input image that contain normal structures and at the same time overanalyzing the remaining portions, that is, the FARs.

The preliminary results as presented in the previous section are quite encouraging, but much of the work remains. In the upcoming months, we intend to investigate a number of open issues, such as tailoring the fractal encoding scheme for mammographic images, analyzing computational overhead of this scheme, and evaluation and implementation of other segmentation techniques (e.g., [7,8]) and classification methodologies.

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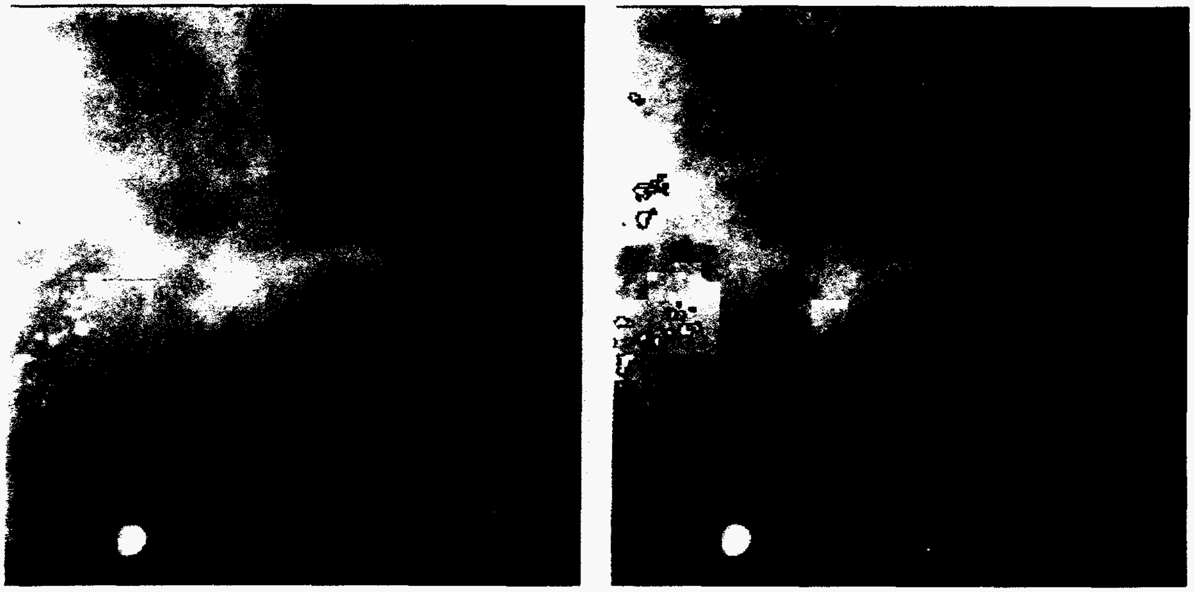
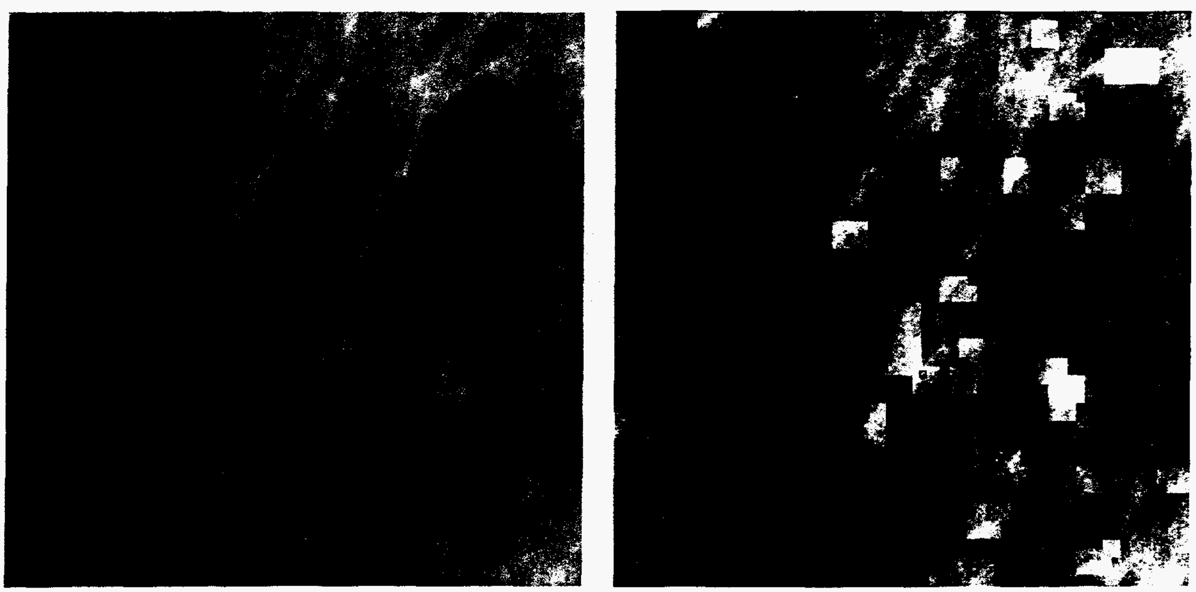


(a) (b)

Fig. 5. (a) A mammographic image with clustered microcalcifications on the left side and a large, circular anomaly in the lower-left corner. (b) The original mammographic image showing the results of the segmentation technique (green and red overlays) and FARs generated by the proposed fractal encoding scheme (highlighted, rectangular regions). Note that three false detections (red overlays) would be eliminated by processing only the FARs, and that FARs represent only 10% of the original data (90% reduction).



(a) (b)

Fig. 6. (a) A mammographic image with no microcalcifications. (b) The original mammographic image showing the results of the segmentation technique (green and red overlays) and FARs generated by the proposed fractal encoding scheme (highlighted, rectangular regions). Note that seven false detections (red overlays) would be eliminated by processing only the FARs, and that FARs represent only 15% of the original data (85% reduction).

Summary Page

1. What is the application area of the work reported in this paper?
   Medical Image Processing and Analysis
2. How far has this work progressed to date?
   The described work marks the completion of about 25% of our overall objectives.
3. What is the primary significance of this work?
   This work describes a synergistic paradigm that utilizes new methodologies together with previously developed techniques to promote a higher degree of accuracy in computer-aided diagnosis of mammograms with an increased overall throughput. The process of accomplishing these goals is initiated by the fractal encoding of the input image, which gives rise to the generation of focus-of-attention regions (FARs). The primary thrust of this work is to demonstrate that by considering FARs, rather than the entire input image, the performances of the ensuing processes (i.e., segmentation, feature extraction, and classification) are enhanced in terms of accuracy and speed.
4. How is this paper related to previously published work?
   This work has not been published previously.