A Region Growing Segmentation for Detection of Microcalcification in Digitized Mammograms

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Abstract

This paper presents an approach for detecting microcalcifications in digital mammograms. The microcalcifications appear in small clusters of few pixels with relatively high intensity compared with their neighboring pixels. The processing scheme used here focuses on detection of microcalcification in a very weak contrast to their background and presents a computerized technique to identify the microcalcification masses by extracting various discriminating features using the image processing and analyzing algorithms. Preliminary experiments indicate that further studies are needed to investigate the potential of employing region-based segmentation as a tool for detecting microcalcifications in digital mammograms.

Index Terms: *Breast cancer, digital mammography, segmentation, microcalcification detection.*

1. INTRODUCTION

Cancer is not just one disease but also rather a group of diseases. All forms of cancer cause cells in the body to change and grow out of control. Most types of cancer cells form a lump or mass called a tumor. The tumor can invade and destroy healthy tissue. Cells from the tumor can break away and travel to other parts of the body. There they can continue to grow. This spreading process is called metastasis. When cancer spreads, it is still named after the part of the body where it started. Most kinds of cancer are named after the part of the body where the cancer first starts. Breast cancer begins in the breast tissue. For example, if breast cancer spreads to the lungs, it is still breast cancer, not lung cancer.

According to the Tata Memorial hospital, Mumbai the breast cancer has been reported to occur in 1 woman out of 1000 women (1974-1978). It is continuing to increase rapidly every year, today it occurs in 1 woman out of 10 women. In American women breast cancer has the highest incidence rate i.e. 1 woman out of 9 women and is second only to lung cancer in cancer deaths. For the women age's 40-54 breast cancers is the leading cause of death.

Breast cancer is the most common cancer in women. Breast cancer is a "malignant neoplasm of the breast". A cancer cell has characteristics that differentiate it from the normal tissue cells with respect to: the cell outlines, shape, structure of nucleus and most importantly its ability to metastasize and infiltrate. When this happens in the breast it is commonly termed as 'breast cancer'. X-ray mammography is the most common technique used by radiologists in the screening and diagnosis of breast cancer in women.

A mammogram is a radiograph of the breast tissue. It is the non-invasive means of examining the breast, commonly searching for the breast cancer. Hard lesions with uneven might be reason for follow up procedures. A fat containing mass looks radio lucent on the mammograms, while calcification is small calcium deposit that can be detected on a mammogram.

Minute calcifications are called microcalcification and bigger ones are termed as macrocalcifications [1], [2]. Recent studies have shown that mammography is sensitive in screening and diagnosis of breast cancer with a high false-positive rate [3]. Considering the traumatic nature and cost of biopsy, it is desirable to develop computer technique to detect the microcalcification. Such methods may be helpful in performing initial screening or second reading of mammograms, and may lend objective tools to help radiologists in analyzing difficult cases. It is known that a small but significant number of cancer cases detected in screening program have prompt visible in earlier detections [4]. These cases represent screening errors or limitations, and may occur due to lack of an adequate understanding of perceptual features of breast abnormalities as apparent on mammograms.

In this study, an algorithm is implemented to separate the microcalcification masses from the digital mammography images.

2. THE MAMMOGRAM DATABASE

The mammogram images used in this study were obtained from a private clinic consisting of 40 images and 30 images from Mammographic Image Analysis Society (MIAS).

The technical equipment used for the image acquisition included a high-resolution digital scanner (600x1200dpi) and an acquisition hardware/software system running on a Pentium system.

3. ENHANCEMENT OF MAMMOGRAMS

The basic need for enhancement in mammography is to increase the contrast, especially for dense breasts. Contrast between malignant tissue and normal dense tissue may be present on a mammogram but below the threshold of human perception. Similarly, microcalcifications in a sufficiently dense mass may not be readily visible because of low contrast [5]. As a result, defining the characteristics of microcalcifications is difficult (fig.1).

Conventional image processing techniques do not perform well on mammographic images. The large variation in feature size and shape reduces the effectiveness of classical fixed neighborhood techniques such as unsharp masking [6]. Fixed neighborhood or global techniques may adapt to local features within a neighborhood, but do not adept the size of the neighborhood to local properties. Alternatively, they modify the image depending on global properties, such as the image spatial-frequency spectrum, which may not be representative of a small region of interest in the image. Many images, including mammograms, have isolated regions, which are the primary feature of interest. These features can vary widely in size and shape, and often cannot be enhanced by fixed neighborhood or global techniques. There are two possible approaches to enhancing mammographic features. One is to increase the contrast of suspicious areas as stated earlier, and the other is to remove background noise.

The "region-based image processing" technique which adapts to image features and enhances these features with respect to their surroundings, regardless of the shape and size of the features. In adaptive-neighborhood or region-based image processing, a neighborhood is defined about each pixel in the image, the extent of which is dependent on the characteristics of the image feature in which the given pixel is situated. This neighborhood of similar pixels is called a *region*. If properly defined, regions should correspond to image features.

Fig. 1: Original Mammogram Image

Then, image-processing procedures can be applied on an image feature basis, rather than pixel-by-pixel. There are two classes of regions: non overlapping regions, which are they disjoint segmentation of an image with subsequent enhancement of the segments would result in noticeable edge artifacts and an inferior enhanced image. Their method uses each pixel in the image as a seed to grow a region. The extent and shape of the region adapt to local image gray-level variations, corresponding to an image feature. The contrast of each region is calculated with respect to its individual background. Applying an impirical transformation based on the seed pixel value of each region, its contrast, and its background then enhances contrast. The objective of this scheme is to enhance the quality of "difficult" mammograms to allow the radiologists to make their diagnosis with more confidence. In order to achieve this objective, a high-resolution digitization is maintained throughout the processing procedures.

Removing background noise while preserving the edge information of suspicious areas can enhance a digital mammogram. This approach was investigated by Lai *et al.* [7], who used four selective averaging schemes and a modification of median filtering called *selective median filtering*.

A selective median filter is defined as follows: Given a window W(i,j), centered at image coordinates (i, j), the output of the selective median filter is

$$x_{i,j} = \text{median}\{ x_{r,s} : (r, s) \in N(i, j), \tag{1}$$

$$\text{and } | x_{r,s} - x_{i,j} | < T \} \tag{2}$$

and where $x_{i,j}$ is the image intensity at (i, j), N(i, j) is the area in the image covered by the window W(i,j), and T is a threshold.

In computing the median, the set of pixels is restricted to those with a difference in gray level no greater than some threshold T. Adjusting the parameter T can control the amount of edge smearing. If T is small, the edge-preserving power of the filter is strong, but its smoothing effect is small. If T is large, the filter behaves the other way around. The mammogram image after applying median filter is shown in fig2.

Fig. 2: Mammogram image after applying Median Filter

4. EDGE DETECTION

The most common approach for detecting the meaningful discontinuity in gray level is "Edge detection" .The edge is the boundary between two regions with relatively distinct gray levels. If an image consists of objects of interest displayed on a contrasting ground an edge is a transition from background is called strength of the edge. The edge holds the information in the image like position of item, size, shape and texture [8].

The change in gray level from one pixel to the nest can be used to emphasize or detect abrupt changes in gray level in the image. Since the edges of the object in a scene often produce high changes, these changes are called as 'edge detectors'. The popular mask detectors are QUICK, KIRSH, SOBEL, PERWITT, etc.

Fig. 3: Edge detected

Sobel edge detector combines uniform smoothing in one direction with edge detection. The Sobel method finds edges using the Sobel approximation to the derivative. It returns edges at those points where the gradient is maximum. To accentuate the edges in the image (fig.3), Sobel edge detector method is applied. The edges in the original image produce high gray levels in the image as shown in fig 3.

The first step in computerized image analysis is to divide the image into regions that corresponds to various objects in the image, or possibility to the parts of these objects. Then various features such as size, shape, color and texture are measured for these objects or regions and are used as inputs in classification procedures.

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Fig. 4: Mammogram processed with CLAHE

Fig. 5: Edge-detected image after applying the CLAHE algorithm

Fig 6: Segmented breast image after applying region growing segmentation algorithm.

Contrast limited adaptive histogram equalization (CLAHE) is a special class of adaptive histogram equalization. Adaptive histogram equalization maximizes the contrast throughout an image by adaptively enhancing the contrast of each pixel relative to its local neighborhood. This process produces improved contrast for all levels of contrast in the original image. For adaptive histogram equalization to enhance local contrast, histograms are calculated from small regional areas of pixels, producing local histograms. These local histograms are then equalized or remapped from the often-narrow range of intensity values indicative of a central pixel and its closest neighbors to the full range of intensity values available in the display.

The digital mammogram processed with CLAHE, lesions appear obvious to the background and the image detail is very good. This algorithm is useful for radiologists to see subtle edge information, such as spiculation.

5. DETECTION OF MICROCALCIFICATIONS

Computer aided detection of microcalcifications in digital mammograms has been attempted by several researchers in the past [9],[10],[11]. The objective is to extract the suspicious areas from a mammogram and provide location information on certain microcalcifications of predefined shapes and sizes to radiologists for further examination [12]. They derived an adaptive threshold function from morphological operations. The following characteristic features of the microcalcifications were pertinent in deriving the adaptive threshold function: granular form, casting form, microcalcification size, and microcalcification density. The threshold set is controlled by the index numbers in the skeleton of shapes, which represent microcalcifications in mammograms.

These steps can be summarized as follows: 1) preprocess a gray-level mammogram to smooth out background noise, 2) obtain the skeleton information of microcalcifications and determine the shadow size from the skeleton using morphological operators, 3) select the threshold value based on the size of microcalcifications, 4) classify the suspicious areas based on predefined shapes and sizes of microcalcifications, and reconstruct the gray levels around only the suspicious areas. Steps 3) and 4) need a rule-basethat is provided by expert radiologists.

An observation from these studies on microcalcification detection is that local filtering techniques require the fine-tuning of several parameters related to local image statistics and they frequently result in a large number of false positives. On the other hand, the application of morphological operators requires *a priori* knowledge of the resolution level of the mammograms in order to determine the size and shape of the structuring elements to be used. Besides manual adjustment of the detected areas, these techniques also tend to rely on many stages of heuristics attempting to eliminate false positives.

6. SELECTION OF FEATURES

It is well established that benign masses are usually round or macro-lobulated in appearance. On the other hand, microcalcification posses rough or irregular boundaries including micro-lobulations, spicules and concavities [12].

In computerized analysis it is desirable to classify the objects using robust features, which are independent of scaling, translation and rotation. After segmentation and detecting the boundaries following features are believed to be helpful in the microcalcification of mammograms and are incorporated in the presented work: area, perimeter, median axis, and thinness Ta & Tb(table 1).

Perimeter

Perimeter (p) a region is equal to the total length of a set of line segments connecting the centers of all these boundary pixels in sequence around the region. The algorithm computes the perimeter of a calcification by counting the number of region pixels that have at least one non-region neighbor.

Area

The area (A) in the object is just the count of the ones n the image array.

$$A= n[1] \tag{3}$$

Where n[] represents the count of number of the patterns within the parenthesis.

Thinness

Thinness Tb is a simple measure of contour complexity versus enclosed area defined as

$$Ta = (p^2 / A-4\pi) \tag{4}$$

$$Tb = D / A \tag{5}$$

Calcification is characterized partially by the irregularity. The irregularities in the calcifications computed by an index Tb. Where p is perimeter, D is the diameter & A is area of calcification.

Mar

Minimum aspect ratio (MAR) is the ratio of length by width.

$$MAR = L / W \tag{6}$$

Where L is the length and W is the width.

The determined features are shown in below table.1

Table1: Details of the features used for calcification.

p	A	D	L	W	MAR	Ta	Tb
16	90	8.6023	7	5	1.4	3.3061	0.095581
7	40	2.8284	2	2	1	1.7861	0.070711
10	50	5	3	4	0.75	2.6714	0.1
7	35	2.8284	2	2	1	2.1842	0.080812
20	218	5.6569	4	4	1	1.9471	0.025949
19	157	8.4853	6	6	1	2.4994	0.054046
7	38	2.8284	2	2	1	1.9266	0.074432

7. RESULTS

The extracted features are used for detection of microcalcification. Experimental results showed that the above algorithm is applied on 40 images; the success rate obtained is 92.5%as indicated below.

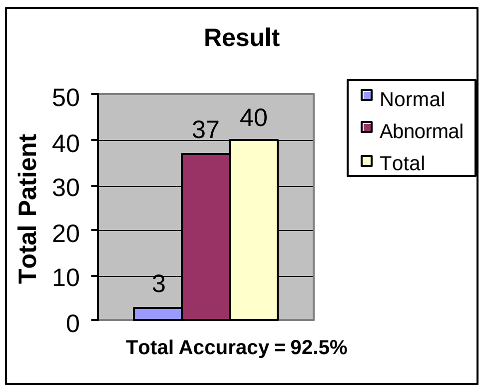

Fig. 7: Result

8. CONCLUSION

The preliminary experiments presented in this paper indicate that the features extracted like area, perimeter, diameter, thinness &min. aspect ratio are very important for detection of microcalcification. In this paper we have analyzed the effectiveness of a number of shape factors in distinguishing microcalcification. The simple measures of thinness Ta & Tb provides a high level of accuracy in this task achieving 92.5% accuracy. In this work we use manual input, we are developing method for automatic detection of microcalcification. A supplementary method with artificial intelligence, ANN will realize an automated computerized technique for detection of microcalcification.

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