A COMPARISON OF CLUSTERED MICROCALCIFICATIONS AUTOMATED DETECTION METHODS IN DIGITAL MAMMOGRAM

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ABSTRACT

This paper presents the comparison of three automated methods for an early detection of breast cancer. It specifically detects clusters of microcalcifications (MCCs), which are associated with a high probability of malignancy. The proposed methods are based on several image processing concepts, such as morphological processing, fractal analysis, adaptive wavelet transform, local maxima detection and high-order statistics (HOS) tests. We apply these methods on a set of mammograms (MIAS database) to test their efficiency and computation time. It shows that the HOS test proved to be the most efficient, and give reliable results for every mammogram tested.

1. INTRODUCTION

The weakest link in breast cancer diagnosis has always been the radiologist who must find a lesion and make a diagnosis. However, lately, researchers and clinicians agree that digital mammography has potential advantages where advanced image processing can improve the odds of mammograms in detecting breast cancer earlier. Digital mammography refers to the application of digital system techniques on digital mammogram. Furthermore, it also leads itself well to Computer-Aided Diagnosis (CAD) system, where automated methods used are based on algorithms that enable the computer to highlight any suspicious areas that could be MCCs, masses or other signs of cancer. A radiologist can refer to the automated system for a second opinion, as it is often difficult to distinguish malignant from benign tissue [1].

Clustered microcalcifications (MCCs) on digital mammograms are an important early sign of breast cancer. An early detection gives the patient a good chance of survival, whereas a late detection can be fatal and often end in the death of the patient. MCCs appear as tiny, circular deposits of calcium, which can vary in size from 0.01 mm^2 to 0.1 mm^2. Because of their sizes, MCCs are difficult to be detected by radiologists, so the radiologists need to use an automated diagnosis system to assist them in the detection.

Various types of techniques have been proposed to detect the present of clustered MCCs in digital mammograms: classical image processing techniques, wavelet-based techniques, features extraction and neural network techniques [1], Laplacian of Gaussian filtering, morphological approach, fractal analysis and HOS test [5]. In this paper, we study a comparison of morphological approach, fractal analysis and high order statistical test in term of their efficiency and computation time. Comparing performances obtained for these methods, the most efficient and reliable method is then recommended for the detection of clustered MCCs.

2. APPROACH AND METHOD

The mammographic images used in this experiment are provided by the MIAS MiniMammographic database, University of Portsmouth, UK containing different digitized images, which can be either normal or having one or more clusters of MCCs. The images are digitized at a size of 1024 $\times$ 1024 with 256 gray levels.

2.1. Preprocessing

The purpose of this stage is to preprocess the digitized images for breast region extraction. This is due to the fact that approximately or more than 30% of the mammogram is dark breast background, which provides very little information for diagnosis. In order to make the detection more efficient, extracting the regions of interest (ROIs) is the first step of computer automation. Besides, it also saves processing time and reduces false detection. To extract the breast region we use a block region growing method [2].

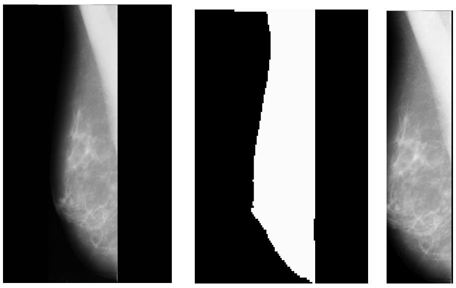

Figure 1(a): *Original image* *Figure 1(b):* *binary mask obtained by region growing method* *Figure 1(c)* *Reduced size image*

Figure 1: Preprocessing stage

2.2 Morphological Approach

Microcalcifications appear on the mammographic images as circular bright spots, and a calcification has approximately a size of 20 pixels on each mammogram. They also have low local contrast. The properties of MCCs enable them to be detected through morphological operators.

The morphological approach consists of isolating the breast background from the microcalcifications using successive openings and p-tile thresholding. The opening operation is grayscale erosion followed by grayscale dilation on the original image [3,7].

The grayscale dilation of an image f by a structuring element b is defined as follows:

$$(f \oplus b)(s,t) = \max\{f(s-x, t-y) + b(x,y) \mid (s-x, t-y) \in D_f \; (x,y) \in D_b\} \quad (1)$$

where D_f and D_b are the domains of f and of b respectively.

The grayscale erosion is similar operation by taking the minimum value instead of the maximum and is defined as follows:

$$(f \Theta b)(s,t) = \min\{f(s+x, t+y) - b(x,y) \mid (s+x, t+y) \in D_f \; (x,y) \in D_b\} \quad (2)$$

In morphological analysis we first apply an opening to the original image to keep the breast background, then we subtract this background from the original image and we threshold the result image from the values of its histogram.

2.3 Fractal Analysis

The fractal analysis separates the MCCs from the breast background by their texture properties. Fractal dimension actually can define the roughness of an area. As the roughness of a calcification area is different from the roughness of the breast background, the fractal dimension can be used to determine whether or not the area is a calcification area.

For the estimation of fractal dimension, we subdivide the image into several sub-images and then calculate the fractal dimension for each sub-image. We choose to calculate the fractal dimension on each 8 x 8 block of the original image. This size of blocks fits the dimensions of a clustered MCCs. We choose a scaling factor of $r = 8$ for the calculation of fractal dimension. Actually the best choice for r is the last iteration where dilation and erosion still contain MCCs, just before these ones completely disappear. To calculate the fractal dimension we use the Blanket Method developed by Mandelbrot and extended by Peleg for estimating the fractal dimension of a surface area [2].

The fractal dimension of a grayscale image is usually between values 2 and 3**.** For a rough image, the fractal dimension is a bit higher than for a smooth image [8]. In our experiments, we obtained the average fractal dimension of a breast area without MCCs is approximately 2.3, though the average fractal dimension for an area containing MCCs is rather about 2.8.

2.4 High Order Statistics (HOS) based on local maxima detection and adaptive wavelet transform

As the clustered MCCs are isolated bright spots on the mammogram, they correspond to local maxima on the image. In this method, we first detect the local maxima of the image, and rank the maxima according to a high order statistical (HOS) test performed over the subbands obtained by the adaptive wavelet transform [4-6].

The MCCs are different in nature than regular breast tissue, so that they produce outliers in the subband domain. We use this fact to rank the local maxima according to the fourth order statistical test estimated in the neighborhood of each local maximum [5]. This also may eliminate the maxima due to small variations in the pixel values and smooth edges of the image.

The HOS test is a robust indicator of the gaussianity of an area. It is based on sample estimates of the first four moments I_1, I_2, I_3 and I_4 of the prediction errors.

In this test, we estimate the fourth-order statistics H in a M by N window around each local maximum location from the quarter size image

$(|H|+|V|+|D|)[m,n]$ obtained by adaptive wavelet transform. The maxima are ranked according to their H value.

Adaptation of the predictor coefficients used in HOS test is carried out by Least Mean Square (LMS) type algorithm. The scalar μ determines the step size of the adaptive algorithm [6]. In previous study [5], fixed scalar was used during adaptation in LMS algorithm for MCCs clusters detection. However, in our case, the value of μ is determined according to the range of input as in [6].

3. RESULTS AND DISCUSSION

Table 1 and Table 2 below show the comparison of the three different methods in terms of computation time and efficiency. Computation time is defined as time taken by each method to execute programs for MCCs clusters detection. Whereas efficiency is an ability of the methods measured in term of percentage to detect MCCs clusters.

Table 1:Computation time

Computation time for each method :	
Morphological analysis	3’20”
Fractal dimension analysis	7’20”
Complete HOS test	9’20”

Table 2: Efficiency of the different methods

Efficiency of the different methods on the database (% clusters detected):	
Morphological analysis	74%
Fractal dimension analysis	92%
Complete HOS test	99%

4. CONCLUSION

We realized automated detection methods for early detection of breast cancer, and tested several different approaches on digital mammograms using a set of mammograms from the MIAS database. The methods and approaches have different computation time and efficiency of percentage MCCs detected, as shown in above tables; the two most efficient methods for the clustered MCCs detection are the fractal analysis and the HOS test, yet these methods are quite long to compute.

These two methods are most recommended since we can rank the clustered MCCs by their fractal dimension (the bigger the fractal dimension, the rougher the surface), and by their statistical properties (the bigger the HOS value, the more the cluster derives from gaussianity). However, the HOS test seems to be the most efficient, and give reliable results for every mammogram tested.

5. REFERENCES

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Figure 2(a):
Original image

Figure 2(b):
Background image

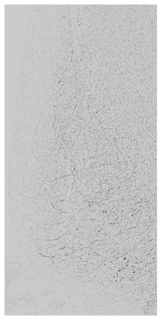

Figure 2(c):
Difference image

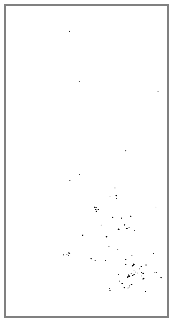

Figure 2(d):
Thresholded image

Figure 2: Morphological Approach

Figure 3(a)
Original image

Figure 3(b)
Fractal dimensions image

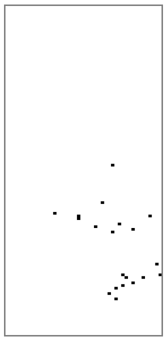

Figure 3(c)
Thresholded resulting image

Figure 3: Fractal Analysis

Figure 4(a):
Original image

Figure 4(b):
HOS test image
the dark points correspond
to high HOS values

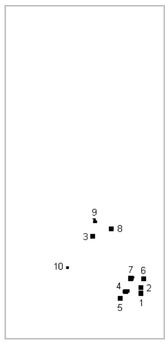

Figure 4(c):
HOS test thresholded:
the local maxima are ranked
according to their HOS value

Figure 4: HOS Test based on Local Maxima Detection and Adaptive Wavelet Transform