MODIFICATION OF MAMMOGRAPHY SLIDES (MAMMOGRAMS) FOR DETECTION AND EARLY DIAGNOSIS OF BREAST CANCER USING WAVELET TECHNIQUES AND NEURAL NETWORKS

Zahra Maghsoodzadeh Dr. A.R. Zolghadr-e-asli Dr. V. Adib
Shiraz University Shiraz University Shiraz University of Medical
Department of Electrical Eng. Department of Electrical Eng. Sciences
maghsoodzadeh@yahoo.com Correspond. author: zolghadr@shirazu.ac.ir

ABSTRACT: In this paper, some modifications of mammogram for the detection of microcalcifications are explained. This can be achieved in two steps. At first stage, wavelet transformation and two statistical properties are used to detect the abnormal pixels and at second stage, a set of ten characteristics are applied to images to cancel some erroneous detected pixels and improving the final result. Therefore, in both steps, a neural network with a hidden layer trained by some vectors is used. The results are shown in FROC curves (Free Response Operating Characteristics). For more details, a typical process is explained in the paper. It should be mentioned that the main difference of this research with previous once, in addition to improving results, is use of a real database which is the mammograms of the local patients at Shiraz hospital (Faghihi).

Keywords: CAD: Computer Aided Diagnosis, FROC: Free Response Operating Characteristics, Mammogram: Mammography slide.

1 INTRODUCTION

Breast cancer is one of the most important reasons of female death. Diagnosis in the initial stages is very important to cure the disease. Although mammography and sonography are two efficient ways of detection in the first steps, their disadvantage is their inefficiency in distinguishing between probable malignant and benign disorders which requires tissue sampling, short time following up and repeating the photography. In this paper, we present a way to digitally process and modify mammography slides by using computer developments, image processing techniques, wavelet transforms and artificial neural networks. Indeed, minimizing the duration of diagnosis is our general aim. As in some cases one may go over 3-6 months to diagnose her disease which is a high risk. We should note that CAD (computer aided diagnosis) is just an adjuvant way for the detection of the disease and then its treatment and will never replace a radiologist.

2 MEDICAL PERSPECTIVE

To construct a system for the detection and modification of mammography slides, it is important to have some basic medical knowledge in this area. It is also important to investigate how a skillful radiologist works and we have to work along an expert in this area. In this section a presentation of mammographic issues from a medical point of view is given. The breast is a complex organ consisting of many different types of tissues.[1]

When a mammogram of the breast is taken, different tissues show different shades of gray color
depending on the level of absorbed radiation. Cancer is a disease in which abnormal mutated cells in some organs grow out of control. Healthy cells reproduce themselves continuously throughout life, growing new tissues and replacing old or damaged ones. This is a normally controlled and orderly process. However, sometimes this orderly process is disturbed and cells begin to reproduce themselves in an abnormal way, building a tumor. [1, 6, 5]

The breast cancer is a prevalent cancer among women that often is beginning from lobules and duct. It is divided to invasive and non-invasive types. Mammography and clinical test is a considerable method to recognize the breast cancer. The breast tissue is soft, heterogeneous, and different in everybody but is similar more in the both breast of each person.

2.1 Signs of Cancer in a Mammogram

• The Tumor: The attenuation of a tumor may vary depending on the type of tumor.
• Asymmetry: Normally the two breasts of a woman are very much alike. Any asymmetry or irregularity between the parenchyma of the two breasts should cause suspicion, since it may be a sign of cancer.
• Microcalcifications: Microcalcifications are microscopic grains of calcium produced by the cells as a result of some benign or malignant process. The calcifications have much higher attenuation compared to the surrounding tissues and absorb more radiation. Therefore the calcifications are visible as bright spots in a mammogram.
• Skin Thickening

The radiologist compares the images of the left and the right breasts. Normally the two breasts of the same woman are like mirror-images of each other. Then the radiologist studies the pectorals area, the lower parts of the breasts, and the mamilla searching for any visible distortions. If the radiologist discovers anything suspicious, more examination is performed. Clinical examination, mammography, ultrasound and needle biopsy may be used in this examination. [1, 12]

In this paper we consider only Microcalcifications among other factors mentioned above.

3  NEURAL NETWORK & WAVELET TRANSFORM

In the past few years, wavelet transforms and neural networks have been successfully used in many applications. In this section, we briefly introduce these two techniques. [13]

3.1 Wavelet transform

The wavelet bases \( \psi(x) \) are functions generated from a kernel function \( \psi(x) \) called the mother wavelet, by dilation and translation as follows:

\[
\psi_{2,j}(x) = \psi_{2,j}(x - 2^j t) = 2^j \psi(2^j x - t)
\]

Where \( s \) and \( t \) are dilation and translation parameters. The mother wavelet \( \psi(x) \) must satisfy the condition that either:

\[
\int \psi(x) dx = 0
\]

or

\[
\int \left| \hat{\psi}(w) \right|^2 |w| < \infty
\]

Where \( \hat{\psi}(w) \) is the Fourier transform of \( \psi(x) \). Wavelet decomposition is performed by convolving the signal \( f(x) \) with the wavelet bases \( \psi(x) \); that is,

\[
\langle f(x), \psi_{2,j}(x) \rangle = \int f(x) \psi_{2,j}(x) dx
\]

Many different wavelet bases have been constructed and correspond to multiresolution analyses. In multiresolution analysis, let \( \phi(x) \) and \( \psi(x) \) be the scaling function and associated mother wavelet; the computation of \( \langle f(x), \psi_{2,j}(x) \rangle \) is then formulated as follows:

\[
\langle f(x), \psi_{2,j}(x) \rangle = \sum_k h(k - 2t) \langle f(x), \psi_{2,j}(x) \rangle
\]

and

\[
\langle f(x), \psi_{2,j}(x) \rangle = \sum_k g(k - 2t) \langle f(x), \psi_{2,j}(x) \rangle
\]

where \( h(t) \) is a low-pass filter \( g(t) \) is a high-pass filter and \( g(t) = (-1)^j h(1 - t) \). We could find that

\[
\langle f(x), \psi(x) \rangle \text{ at } 2^{2+k} \text{ scale could be achieved by passing } \langle f(x), \psi(x) \rangle \text{ at } 2^k \text{ scale through the low-pass filter } h(t). \]

Similarly, we could find that

\[
\langle f(x), \psi(x) \rangle \text{ at } 2^{2+k} \text{ scale could be achieved by passing } \langle f(x), \psi(x) \rangle \text{ at } 2^k \text{ scale through high-pass filter } g(t). \]

A 2-D subband filter scheme is used when applying the wavelet transform for image applications. Figure 1 depicts an example of the 2-D subband scheme. First, a 1-D decomposition filter is applied to each row of the image signal and then two filtered
subimages, L and H, are generated by down-sampling. The size of each subimage is half of the original image size. The same 1-D decomposition filter is applied to each column of subimages L and H, and four subimages, LL, LH, HL and HH, Fig. 1. An example of 2-D representation of the wavelet decomposition is generated by down-sampling. The size of each subimage is one quarter of the original image size. [13, 1, 11, 9]

Fig.1. An example of 2-D representation of the wavelet decomposition

3.1 Neural networks

A neural network is a model that simulates the functions of biologic neurons. The ability of a single neuron could be greatly improved by connecting multiple neurons in a layered network called MLP (multilayered perception) or feed forward artificial neural network. [13,9]
The main goal of an image-recognition system using neural networks is to achieve the purpose that evaluates the input signals to the desired outputs correctly.
In the next section, we describe our proposed method for diagnosis of breast tumors in sonographic images. By Training the artificial neural networks used in our algorithm. Training is an important step which means that the network with knowledge about the desired response adjust its behavior in order to have a better response with the same input in the next moment. In the other words, the network is trained to develop its behavior progressively. [9, 13, 7, 8, 5]

4 DESIGNING THE SYSTEM

The microcalcifications appear with the approximate size of 0.01 to 0.05 mm in mammogram. Their shapes differ by uniform light distribution. Applying wavelet transforms will cause a set of HH and HL+LH subimages to be produced. The smaller the size of the microcalcification, the higher the frequency and visa versa. The results of wavelet transforms are combined together to give a characteristic for detection. The easiest way to carry out this is using a threshold level.
In the first stage, four characteristics were used: two of them are wavelet coefficients and the other two are statistical characteristics of gray levels. Using these characteristics signify the objects which can be counted as microcalcifications. In the second stage, approximately ten characteristics are calculated by which the true microcalcification points are distinguished.

Nearly 30% of a mammogram is breast tissue. Considering this fact, only this part is selected and isolated from mammogram. The advantages of this selection are: 1.Reducing the calculation time. 2. Omitting FPs created by the contour of the breast.
For training the neural network system, we selected and scanned many images in the mammography section of Dr. Faghihi Hospital (Iran-Shiraz) during several months.
It should be mention that most papers[2,7] (about 90%) derivate their images from Netherlands Database (DDSM) (accessible from http://www.figmeni.csee.usf.edu), but in this research we have used the images of local patients.

5 PRE-PROCESSING & DETECTING ABNORMAL PIXELS

First, we calculate four properties for each pixel: two wavelet coefficients and two statistical features of gray levels, which are inputs of a neural network.
To obtain wavelet coefficients, we impose a wavelet transform in four different resolutions to each mammogram image (Fig.2). The first resolution image is noise image and the last resolution is mammogram background. Hence, the suitable data of microcalcifications are the second and third resolutions, which are used as parameters of wavelet properties to diagnose each pixel.
Two other properties defined are median contrast and normalized gray level values which are computed as below:

\[ c(i,j) = p(i,j) - \text{median}(y(l,m), l,m \in \text{Window}) \] (7)

\[ s(i,j) = \frac{p(i,j) - \text{mean}(y(l,m), l,m \in \text{Window})}{std(y(l,m), l,m \in \text{Window})} \] (8)

Where p(i,j) is pixel value in (i,j) position, window is a n×n square by center (i,j) coordinate (here we
choose \( n=7 \), \( \text{std} \) is standard deviation of pixels in window, \( c(i,j) \) and \( s(i,j) \) are median contrast and normalized gray level value. Thus for each pixel \((i,j)\) we calculate property vector \( f(i,j) \):

\[
f(i,j) = [w_x(i,j), w_y(i,j), c(i,j), s(i,j)]
\]  (9)

To diagnose probable microcalcifications we use neural networks with two layers. Having output network for each pixel, we get our image named “likeness image”. We compare the number of pixels of the image and the threshold value to get abnormal pixel. The higher value of result, it means more probability of microcalcifications.

![Fig.2. Neural networks at first stage](image)

The result is a binary image, which is 1 for microcalcifications and 0 for healthy pixels. 27 images are used for training a network that detects 1248 microcalcification pixels. 1248 pure pixels are considered in these images. Because for each pixel 4 properties are calculated, the size of training data vectors will be \( 1248 \times 2 \times 4 \).

To train the network, we attribute 1 for microcalcification pixels and 0 for normal ones at the out put as desirable results.

In this stage, some fault microcalcifications pixels may appear that will be omitted by our algorithm, which is explained below.

6 THE PROCESS OF DETECTING MICROCALCIFICATIONS

In the first step, we detected the abnormal pixels possible to be microcalcifications. In the next, we classify the adjacent pixels (4 neighborhoods) to the abnormal objects and omit the single pixels which are often created by noises.

Table 1: I. Regional descriptors, II. Moments, III. Second order histogram

<table>
<thead>
<tr>
<th>No.</th>
<th>properties</th>
<th>categories</th>
<th>Computing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Standard deviation</td>
<td>I</td>
<td>Radial of variance</td>
</tr>
<tr>
<td>2</td>
<td>Area</td>
<td>I</td>
<td>The number of object’s pixels</td>
</tr>
<tr>
<td>3</td>
<td>Compactness</td>
<td>I</td>
<td>( C = \text{perimeter}^2 / \text{area} )</td>
</tr>
<tr>
<td>4</td>
<td>Elongation</td>
<td>I</td>
<td>( \text{Max Axis/Min Axis} )</td>
</tr>
<tr>
<td>5</td>
<td>Shape Moment</td>
<td>II</td>
<td>( \alpha_i = \frac{\text{area} \cdot \text{Max Area} - \text{area} \cdot \text{Min Area}}{\text{Max Area} + \text{Min Area}} )</td>
</tr>
<tr>
<td>6</td>
<td>Invariant Moment</td>
<td>II</td>
<td>[ \frac{1}{n} \sum_{i=1}^{n}</td>
</tr>
<tr>
<td>7</td>
<td>Contrast</td>
<td>III</td>
<td>[ \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha(y_i, y_j) ]</td>
</tr>
<tr>
<td>8</td>
<td>Entropy</td>
<td>III</td>
<td>[ -\sum_{i=1}^{n} \sum_{j=1}^{n} [H(y_i, y_j, d) \log H(y_i, y_j, d)] ]</td>
</tr>
<tr>
<td>9</td>
<td>Angular 2nd-order moment</td>
<td>III</td>
<td>[ \sum_{i=1}^{n} [H(y_i, y_j, d)] ]</td>
</tr>
<tr>
<td>10</td>
<td>Inverse different moment</td>
<td>III</td>
<td>[ \sum_{i=1}^{n} [H(y_i, y_j, d)] ]</td>
</tr>
</tbody>
</table>

In this section, the system defines that a abnormal object is whether TP3 or FP. To do this, ten properties are calculated for each pixel as input of a neural network. These properties are listed in table 1. These properties are divided in three categories: I. Regional descriptors, II. Moments, III. Second order histogram.
A) Regional descriptors:
The properties of them are standard deviation, area, compactness and elongation.

- **Standard deviation** is equal to square root of the variance of the object.
- **Area** is the number of the pixels.
- **Compactness** is calculated by:
  \[
  \text{Compactness} = \frac{\text{perimeter}^2}{\text{area}}
  \]
  In which perimeter is the pixels surrounded around the object.
- **Elongation** is calculated by divided the long main axe of the object to the short one. (Fig 3)

B) Moments:
This has two properties: shape and invariant moments.

- **Shape moment** is fined by:
  \[
  \phi = (\eta_{20} - 3\eta_{02})(\eta_{00} + \eta_{20})^{\frac{1}{2}} - 3(\eta_{21} + \eta_{12})^2
  \]
  \[
  + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})^2 - (\eta_{21} + \eta_{03})^2 \]
  where:
  \[
  \gamma = \frac{p + q + 1}{2}, \quad \eta = \frac{\mu_{pq}}{\mu_{00}}
  \]
  \[
  \mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y)
  \]
  \[
  \bar{x} = \frac{m_{10}}{m_{00}}, \quad \bar{y} = \frac{m_{01}}{m_{00}}
  \]
  \[
  m_{pq} = \sum_x \sum_y x^p y^q f(x, y)
  \]

- **Invariant moment**, which is calculated as below:
  \[
  IM = \left( \frac{1}{N} \sum_{i=1}^{N} [z(i) - m_1]^2 \right)^{\frac{1}{2}} - \left( \frac{1}{N} \sum_{i=1}^{N} [z(i) - m_1]^2 \right)^{\frac{1}{2}}
  \]
  \[
  m_1 = \frac{1}{N} \sum_{i=1}^{N} z(i)
  \]

C) Properties of 2nd order histogram
The first order histogram indicates frequency of assurance the different gray levels in the image. But the second order histogram ( \( H(y_q, y_r, d) \) ) represents distribution of existence of two gray levels, \( y_q, y_r \) with vector distance, \( d \). As the gray levels are defined by 8bit, so this histogram is a 2-D function of 256 × 256 elements.
The calculated properties are: contrast, Entropy, second order angular moment and inverse difference moment.

- **Contrast**, is shown the variation of the images structure as sharpness, accidental. Calculated as below:
  \[
  \text{contrast} = \sum_{y_q=1}^{256} \sum_{y_r=1}^{256} \partial H(y_q, y_r, d)
  \]
  Where \( H(y_q, y_r, d) \) is a second order histogram function and \( \partial H(y_q, y_r, d) = (y_q - y_r) \)

- **Entropy**, a factor of nonuniformity is a calculated as follows:
  \[
  \text{Entropy} = - \sum_{y_q=1}^{256} \sum_{y_r=1}^{256} \left[H(y_q, y_r, d)\right] \log[H(y_q, y_r, d)]
  \]

- **2nd order angular moment**, a stable factor of uniformity is computed as below:
  \[
  m_2 = \sum_{y_q=1}^{256} \sum_{y_r=1}^{256} \left[H(y_q, y_r, d)\right] ^2
  \]

- **Inverse difference moment**: the local homogeneity property is calculated by:
  \[
  \text{IDM} = \sum_{y_q=1}^{256} \sum_{y_r=1}^{256} \frac{H(y_q, y_r, d)}{1 + \partial (y_q, y_r)}
  \]

For \( y_q \neq y_r \)

After computing these properties, we apply them as the input of the two layer neural network, as shown in fig.4. The output value of the network will be between –1 and 1 that shows the probability of being microcalcification. Therefore, comparing this output and the threshold level the abnormal object can be judged to be microcalcification or not.
mammography consisting of microcalcifications and process this image by the first step, then check the abnormal objects and mark the correct abnormal objects.

In the next step we omit the objects which do not have any other objects in their vicinity of 0.5 cm (that is 50 pixels). Then the adjacent objects are classified in clusters.

Table 2: Different threshold levels used in second neural network

<table>
<thead>
<tr>
<th>Name of image</th>
<th>No. of clusters</th>
<th>First Threshold Level</th>
<th>Second Threshold Level</th>
<th>Third Threshold Level</th>
<th>Forth Threshold Level</th>
<th>Fifth Threshold Level</th>
<th>Sixth Threshold Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>M 1</td>
<td>2</td>
<td>2 1 1 2 1 2</td>
<td>1 2</td>
<td>1 2</td>
<td>1 1 1 1 1 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 2</td>
<td>2</td>
<td>2 4 2 1 2 1</td>
<td>2 1</td>
<td>2 1</td>
<td>2 1 2 1 2 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 3</td>
<td>1</td>
<td>1 2 2 1 2 1</td>
<td>2 1</td>
<td>2 1</td>
<td>2 1 2 1 2 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 4</td>
<td>1</td>
<td>1 0 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 0 0 0 0 0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 5</td>
<td>2</td>
<td>1 0 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 6</td>
<td>1</td>
<td>1 3 1 1 1 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 7</td>
<td>1</td>
<td>1 3 3 1 1 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 8</td>
<td>1</td>
<td>1 1 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 9</td>
<td>15</td>
<td>10 4 2 8 1 7</td>
<td>1 6</td>
<td>1 5 0 5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 10</td>
<td>13</td>
<td>9 6 2 6 2 5</td>
<td>2 4</td>
<td>2 4 2 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 11</td>
<td>1</td>
<td>1 1 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 12</td>
<td>1</td>
<td>1 0 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 13</td>
<td>2</td>
<td>2 1 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 14</td>
<td>2</td>
<td>1 3 1 1 0 0</td>
<td>0 0</td>
<td>0 0</td>
<td>0 0 0 0 0 0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 15</td>
<td>1</td>
<td>1 2 2 1 2 1</td>
<td>2 1</td>
<td>2 1 2 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 16</td>
<td>1</td>
<td>1 1 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 17</td>
<td>1</td>
<td>1 0 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 18</td>
<td>1</td>
<td>1 2 0 1 0 1</td>
<td>0 1</td>
<td>0 1</td>
<td>0 1 0 1 0 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 19</td>
<td>9</td>
<td>9 1 0 4 0 4</td>
<td>0 4</td>
<td>0 4 0 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 20</td>
<td>5</td>
<td>5 3 0 5 0 5</td>
<td>0 3</td>
<td>0 3 0 3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 21</td>
<td>2</td>
<td>2 0 0 2 0 2</td>
<td>0 2</td>
<td>0 2 0 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 22</td>
<td>1</td>
<td>1 0 0 0 0 0</td>
<td>0 0</td>
<td>0 0 0 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 23</td>
<td>1</td>
<td>1 2 1 1 1 1</td>
<td>1 1 1 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M 24</td>
<td>2</td>
<td>1 0 0 1 0 1</td>
<td>0 0</td>
<td>0 0 0 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sum</td>
<td>69</td>
<td>58 41 18 45 14 42</td>
<td>12 36</td>
<td>12 34</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Percentage of detected TPs and average of the FPs for different threshold levels.
To evaluate the ability of the algorithm, 24 mammogram images which are not used in training, in the second step of neural network, are applied to compare the results. The results of each applied threshold level are listed in table 2 and 3.

According to the curve, 60.87% of the whole existence clusters with 58.3% of the average error in each image is diagnosed.

By comparing the curve with the results obtained from Strickland algorithm we see that the results are quite fair and the chosen properties are shown the microcalcification and could be detected with neural network effectively. In Strickland algorithm only wavelet transform is used to detect the microcalcification which causes the high FPs.

8  An example

We have applied our algorithm on two cases: 1- an abnormal tissue (with microcalcification). 2- a normal one. The results are shown in Fig.6.

9  CONCLUSION

Breast cancer is a widespread kind of cancer and one of the reasons of the females death. The microcalcification clusters are the most important factor to diagnose the cancer in mammography slides. In this paper, designation and implementation of a CAD system for detecting microcalcifications in mammography images is explained.

A neural network with a hidden layer trained by a number of vectors is used for both steps. The results are shown in FROC (Free Response Operating Characteristics) curves, which show that for each image 60.87% of the total clusters are detected with an average error of 58.3%. By comparing the results of this curve with others, it is concluded that our method shows microcalcifications effectively. We suggest the following propositions for completing above algorithm:

- The figure and the form of distribution of the microcalcification clusters in the mammogram help the radiologist for final diagnose.
- Developing or increasing the number of properties in the second step of algorithm improve the accuracy of detection the micro calcifications.
Fig 6. a: Original image b: tissue with microcalcifications, c: normal tissue
(From the right these images consist of: selected part for processing, magnifying the image, the image after pre processing and the final process which detect the position of microcalcifications.)

10 REFERENCES


