Computer-aided detection of clustered microcalcifications in digital mammograms.

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Abstract
In this paper we propose a new algorithm for the detection of clustered microcalcifications using mathematical morphology and artificial neural networks.
Mathematical morphology provides tools for the extraction of microcalcifications even if the microcalcifications are located on a non-uniform background Considering each mammogram as a topographic representation, each microcalcification appears as elevation constituting a regional maxima. Morphological filters are applied, in order to remove noise and regional maxima that doesn't correspond to calcifications. Each suspicious object is marked using a binary image. The extracted objects are classified using neural networks.

Keywords:
mathematical morphology, neural networks, mammography, microcalcification.

1. Introduction

Breast cancer is the most common form of cancer among women. About 10% of all women develop breast cancer and about 25% of all cancers diagnosed in women are breast cancers [Lau (1991)]. Mammography continues to be regarded as a useful diagnostic tool for detection and diagnosis of breast lesions. The interpretation of a mammogram is often difficult and depends on the expertise and experience of the radiologist. The presence of microcalcifications in breast tissues is one of the main features considered by radiologists for its diagnosis.
In the past several years there has been a considerable interest in developing methods for automatic detection of microcalcifications. Several methods have been proposed in the literature for their segmentation and detection. In this paper we present a new method for automatic segmentation and classification of microcalcifications using mathematical morphology and neural networks.

2.Methods

Mathematical morphology can be defined as a theory for the analysis of spatial structures [Soile (1999)]. It is called morphology because it aims at analyzing the shape and form of objects. The basic tools of mathematical morphology are the morphological operations.
A morphological operation P transforms an image A by means of a structuring element B (which can be chosen by the user) into a new image P (A; B). The basic morphological operations are dilation and erosion [Nachtegael (2001)]. Using the basic morphological operators we can design powerful morphological filters. The basic morphological filters are the morphological opening and the morphological closing. Based on the notion of geodesic distance, we can define geodesic dilation and

geodesic erosion. . A geodesic dilation involves two images: a marker image and a mask image. The marker image grows by iterative geodesic operations while staying always inside the mask image. Given a mask X the geodesic dilation of size $n \geq 0$ of Y within X is the set of pixels of X whose geodesic distance to Y is smaller or equal to n:

$$\delta_X^{(n)}(Y) = \{p \in X \mid d_X(p, Y \ ) \leq n \ \}$$

X is a discrete set of Z^2, $X \subset Z^2$and $Y \subseteq X$

Geodesic dilations and erosions, when iterated until stability, they allow the definition of morphological reconstruction. Grayscale morphological is defined as:
The grayscale reconstruction $\rho_I(J)$of I from J is obtained by iterating grayscale geodesic dilations of J "under" I until stability is reached, i.e.

$$\rho_I(J) = \bigvee_{n \geq 1} \delta_I^{(n)}(J).$$

In morphological image analysis every gray tone image is considered as a topographic relief, where each pixel is associated with an elevation proportional to its intensity. Therefore, many morphological terms stem from geomorphology. So, the dark and light structures of the image correspond to the valleys and the domes of this relief. The plateau located at the top of the domes constitutes regional maxima (denotes maximum). Microcalcifications appear on digitized mammograms as bright spots. These spots are small regions with higher intensity values than their surroundings. Each microcalcification constitutes regional maxima. Figure 1 shows a cluster of microcalcifications and Figure 2 shows the topographic representation of this region, where microcalcifications appear as domes with higher intensity values than the surrounding tissue.

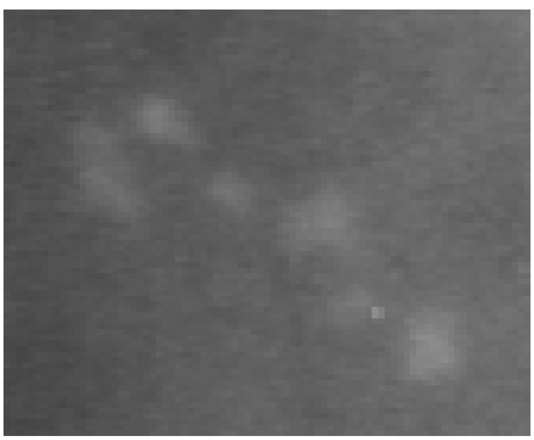

Figure 1 :A cluster of microcalcifications

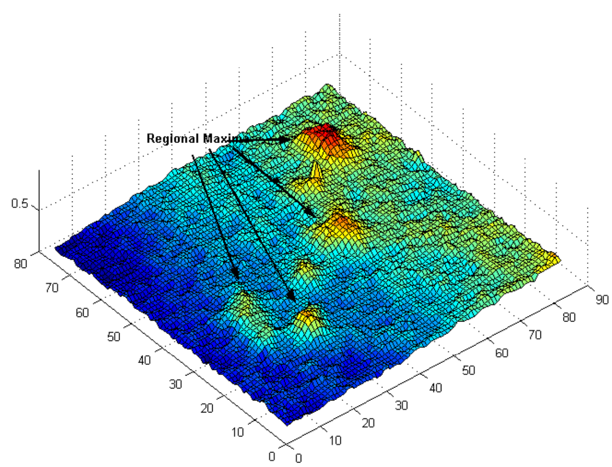

Figure 2:topographic relief

A simple algorithm to extract all regional maximum in mammogram is based on the H-domes transform [Vincent (1993)]. The h-dome transformation is illustrated on Fig. 3. The h-dome transformation extracts light structures without involving any size or shape criterion. The h-domes transformation extracts image regions fulfilling the following criteria:

- Every pixel in the dome has a gray value greater than any of the pixels surrounding it.

- The maximum gray level difference between two pixels in the dome is smaller than or equal to *h*.

The *h*-domes transformation can be defined by:

$$M_h(I) = I - \rho_I(I - h)$$

Where I is the original image, $(I - h)$ represents the result of subtracting a constant value h to the original image, and $\rho_I(I - h)$ the morphological reconstruction of the original image from $I - h$. The choice of h turns out not to be a critical operation, since a wide range of values yields correct results. A study about microcalcifications and their imaging properties [Olson (1998)], showed that region offset average i.e. the difference between average intensity values of every calcification and their surrounding tissue, were similar for all calcifications and only few statistically significant differences were found between benign and malignant offsets. Indeed, choosing a threshold greater than 20 intensity values, all microcalcifications that were used at the testing phase of the algorithm, were extracted.

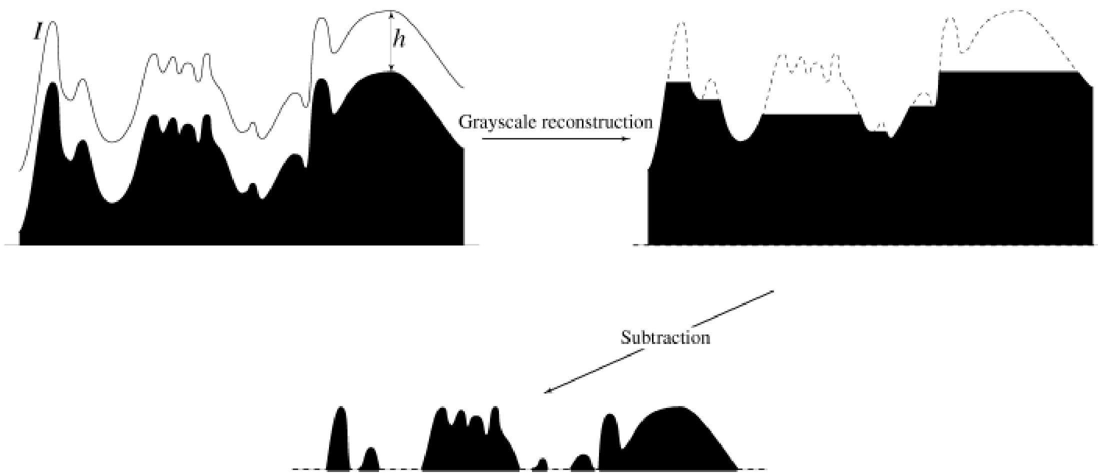

Figure 3: H-domes transformation

The new image contains all the microcalcifications and many more elevations, which doesn't correspond to calcifications, since mammograms are complex images with great number of regional maxima. In order to suppress noise and to reduce the number of the extracted domes, the image is opened using a disk shaped structuring element of radius of two.

After image opening, every mammogram is thresholded using the extended maxima transformation [Soile (1999)]. The extended maxima transformation can be obtained by simply thresholding the h-dome image for values greater than zero. As a result, we get a binary image. A connected-component labeling operation is performed, in order to evaluate the characteristics and the location of every object. Objects smaller than 0.1mm and greater than 2 cm in diameter are discarded. As a second object reduction step, objects that aren't located close to another object, in a region of 1 cm, are discarded.

The binary image is used only for the extraction of the exact location and area of every object. The original image is used for feature extraction, using the binary image as mask for every object.

3.Experimental Part.

For the development of our algorithm we have used the MIAS database, provided by the Mammographic Image Analysis Society (MIAS). The mammograms are digitized at a resolution of 50μm x 50μm. The database contains 25 mammograms with microcalcifications, 12 of them are benign and 13 malignant. The MIAS database provides groundtruth for each abnormality in the form of circles; an approximation of the center and the radius of each cluster of calcifications.

3.1 Feature extraction

The implemented feature extraction procedure relies on the exploitation of the textural characteristics of the extracted objects. One of the simplest approaches for describing texture is to use moments of the gray-level histogram of an image or region [Gonzalez (1993), Theodoridis (1999)]. From the central moments, the mean, variance, skewness and kurtosis are estimated for each object, plus the number of objects found in a region of radius of 2 cm around each object. The features extracted from the original mammograms, are classified using neural networks.

Artificial neural networks (ANNs) are non-parametric pattern recognition systems that can generalize by learning from examples. The most commonly used neural network structure for classification tasks, are multi-layer perceptrons (MLP). Multi layer perceptrons are networks that contain one or more hidden layers, where each neuron includes a nonlinear activation function. In this study we review the performance of a multi layer perceptron. We have evaluated the performance of the MLP using two different topologies, with five and ten hidden nodes respectively.

The number of hidden neurons was estimated experimentally. The neural networks were trained using 107 objects extracted from six randomly selected mammograms. The rest of the mammograms containing microcalcifications and 30 normal mammograms were used in the testing phase. None of the mammograms was used both in the training and testing phase. The performance of the system is evaluated using the FROC curve ("Free response Receiver Operating Characteristic"), where the true positive fraction is plotted as a function of the average number of false positives per image [Karssemeijer (1997)]. The FROC curve is applicable to situations such as diagnostic imaging, that involve multiple detections on a single image. We consider a detection of a cluster as true positive, if 75% of the microcalcifications are correctly detected.

3.2 MLP Performance.

For the case of the MLP we tested two networks with five input units, one output and one hidden layer. More than one hidden layer may be beneficial for some applications, but one hidden layer is sufficient if enough hidden neurons are used [Kim(1999)]. We have evaluated the performance of the MLP using two different topologies, with five and ten hidden nodes respectively.

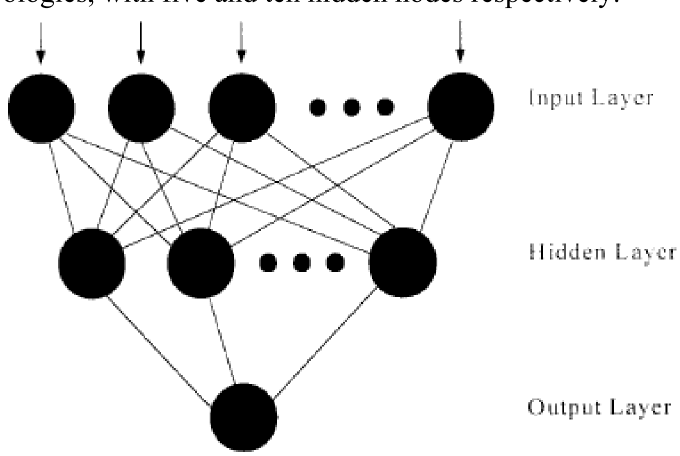

Figure 4: Structure of the three-layer neural network.

A nonlinear sigmoid function is used as the activation function for each neuron and is defined by:

$$y_j = \frac{1}{1+\exp(-u_j)}$$

where u_j is the weighted sum of all synaptic inputs plus the bias, and y_j is the output of the neuron. In the training process, the weights between the neurons are adjusted iteratively so that the differences between the output values and the target values are minimized.

The networks were trained using a back -propagation adaptive learning rate training function, so the learning rate changes during the training process, as the algorithm moves across the performance surface.

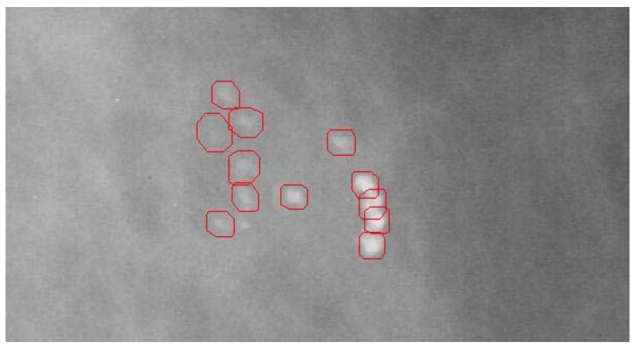

Figure 5
A detected cluster of microcalcifications.

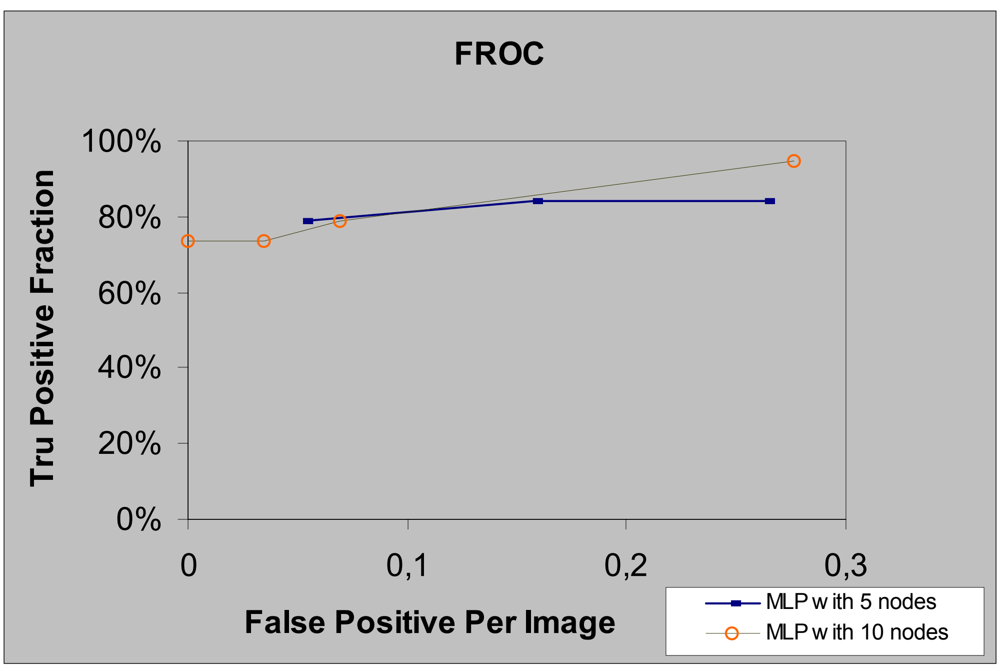

Figure 6. FROC Curve of the MLP

The MLP with ten hidden nodes achieved the best classification rate. The system misclassified one mammogram as normal, achieving a sensitivity of 94,7% with an average of 0.27 false positive findings (FPF) per image. The misclassified image was a mammogram with a single benign calcification.

Using the MLP with five hidden nodes, two mammograms were misclassified as normal, achieving a sensitivity of 84,2% with an average of 0.26 false positive findings (FPF) per image (figure 6).

4.Conclusions

It is well known that mammogram interpretation is a very difficult task even for experienced radiologists. Mathematical morphology proves to be a useful tool for the detection of microcalcifications in digital mammograms. We proposed a new algorithm for the detection of microcalcifications on mammograms. Every suspicious object is marked using a binary image, which is used as a mask for object extraction from the original image. The features of the extracted objects are classified using neural networks. We evaluate the performance of a multi layer perceptron with two different topologies. The best classification rate was achieved using the MLP with ten hidden nodes.

Our feature extraction method and the selected neural network classifiers need to be tested using a larger database in order to perform reliably in clinical situations.

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