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Automatic 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. 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 and finally a feed forward neural network classifies every object achieving a rate of 90% true positive detections with 0.11 false positives per image.

1. Introduction

Mammography continues to be regarded as a useful diagnostic tool for detection and diagnosis of breast lesions. About 10% of all women develop breast cancer and about 25% of all cancers diagnosed in women are breast cancers [1]. The interpretation of a mammogram is often difficult and depends on the expertise and experience of the radiologist. A meta-analysis showed that the sensitivity of screening mammography ranged from 83% to 95% with a false positive rate of 0.9% to 6.5% respectively [2]. Retrospective studies have revealed that approximately 9% of a series of cancers detected at a screening examination were visible on screening mammograms obtained 2 years earlier. Moreover, in another 48% of the cases, a minimal sign was already visible on a prior mammogram. [(4)] Between 30% and 50% of breast carcinomas demonstrate microcalcifications on mammograms, and between 60% and 80% of the carcinomas reveal microcalcifications upon histologic examination [3]. Microcalcifications are tiny granular deposits of calcium that appear on the mammogram as small bright spots. A radiologist must carefully examine the mammogram with a magnifier to locate calcifications, which may be embedded in dense tissue.

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 morphological reconstruction. Microcalcifications are segmented evaluating their topographic representation. The segmented objects are classified using a neural network.

2. Methods

Mathematical morphology can be defined as a theory for the analysis of spatial structures [6]. 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 into a new image P(A; B). The basic morphological operations are dilation and erosion [7]. 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. Both images must have the same definition domain. 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:

$$\delta_X^{(n)}(Y) = \{p \in X \mid d_X(p, Y) \leq n\} \qquad (1)$$

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 reconstruction is a geodesic transformation and 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.

$$\rho_I(J) = \bigvee_{n \geq 1} \delta_I^{(n)}(J). \qquad (2)$$

Every grayscale image is seen as a topographical relief, where each pixel is represented as an elevation proportional to its intensity value. 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. Microcalcifications appear on digitized mammograms as bright spots. These spots are small regions with higher intensity values than their surroundings. Each microcalcification constitutes a 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.) Image maxima are an important morphological feature because it can mark image objects with specific characteristics. Mammograms are complex images with great number of regional maxima. In order to detect microcalcifications we have to evaluate the dynamic of each regional maxima. The dynamics was introduced by Grimaud, as a method, which evaluates the regional maxima and minima of an image. This method does not take into account the size or shape of the structures (valleys, domes), which are evaluated, but unfortunately is very sensitive to noise. A regional maximum M [6,8] of a gray scale image f at elevation t is a connected component of pixels with the value t, whose external boundary pixels have a value strictly lower than t.

Figure 1: A cluster of microcalcifications

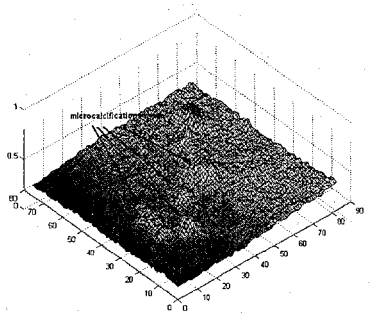

Figure 2: Topographic relief

Considering the union of the maxima at every level t, we get the set all maxima of the image. The dynamics of a regional minimum according to L. Vincent [9] is: Let f be a mapping from $C \subset R^2$ onto R and M be a regional minimum of f. The dynamics of M is the minimal height one has to climb starting from M to reach another minimum of lower altitude. The dynamics of a regional maximum M is defined by considering the path of minimal altitude linking M to another maximum of higher altitude.

A simple algorithm to extract all regional maximum in mammogram is based on the H-maxima transform [6]. The h-maxima transform suppresses all regional maximum whose dynamics is less than a given threshold h. This can be achieved by using reconstruction by dilation of the image I from (I-threshold) : $\rho I(I-h)=\bigvee_{n\geq 1} \delta_I^{(n)}(I-h)$. (3)

Subtracting the reconstructed image from the original image, we get all the regional maximum of the mammogram (h-convex transformation). A study about microcalcifications and their imaging properties [11], 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. The new image contains all the microcalcifications and many more elevations, which doesn't correspond to calcifications. 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. Using grayscale opening we can remove regional maxima that cannot contain the structuring element, but we cannot remove regional maxima of size greater or equal to the structuring element, whose dynamics are very low. This problem can be solved using a fast hybrid grayscale reconstruction. Subtracting a very low constant from the original mammogram creates the marker image. The reconstructed image from the marker image contains all regional maxima with no intensity fluctuations. The combination of grayscale opening followed by a grayscale reconstruction provides a way to remove noise and domes whose dynamics are very low. Figure 3 represents the topographic relief of the opened image, figure 4 represents the image after removing the most important domes, figure 5 is same image after subtraction from the original image and figure 6 after reconstruction. After morphological reconstruction every mammogram is thresholded using the extended maxima transformation. The extended maxima transformation is the regional maxima computation of the corresponding h-maxima transformation. Dynamics with values less than 2% higher than zero background are absorbed. The threshold of 2% was selected since it is the ratio of the just noticeable difference to a reference stimulus (Weber's constant) for visual brightness in human perception [12]. 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. A simple feed forward neural net is enough to classify objects contained in the original image, which, are marked on the binary image.

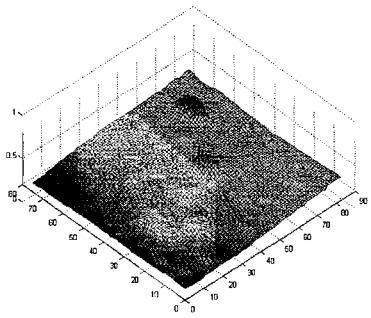

Figure 3. Topographic relief of the opened image

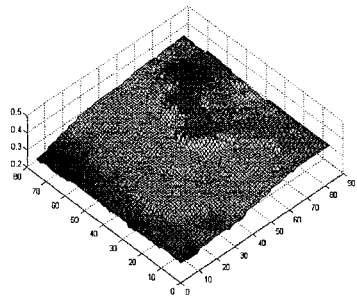

Figure 4: The image after removing the most important domes

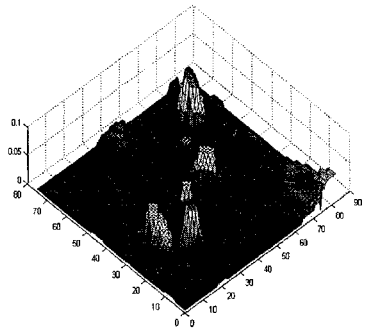

Figure 5: Image after subtraction from the original image

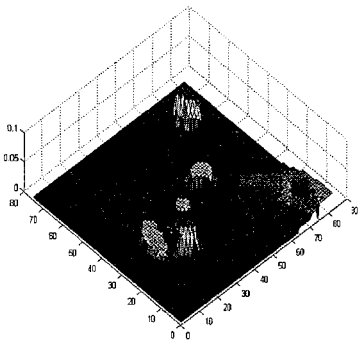

Figure 6: The final image after reconstruction

The neural network used, has five input units, one output and two hidden layers with 15 and 10 neurons respectively. The inputs to the network are:

1. Intensity variance of the object and its external surrounding tissue. The external surrounding region is a border of three pixels around every object.
2. Number of objects found in a region of radius of 2 cm around each object.
3. Mean of the intensity values of every object
4. Mean of the intensity values of the surrounding tissue
5. The difference between the mean intensity values of the object and the mean intensity values of their surrounding tissue.

The network was 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. The learning step size is kept as large as possible while keeping learning stable.

3. Results

In this work the MIAS database, provided by the Mammographic Image Analysis Society (MIAS),was used. 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.

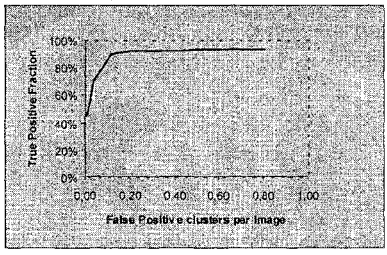

Figure 7: FROC Curve

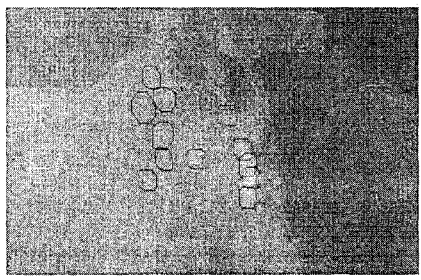

Figure 8: A detected cluster of microcalcifications.

The neural network was trained using 116 objects extracted from five mammograms. Two of the mammograms contained no clusters. 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[14]. The FROC curve is applicable to situations such as diagnostic imaging, that involve multiple detections on a single image (Figure 7). We consider a detection of a cluster as true positive, if 75% of the microcalcifications are correctly detected. The system misclassified two mammograms as normal, achieving a sensitivity of 90% with an average of 0.11% false positive findings per image. Figure 8 demonstrates a region containing a detected cluster of microcalcifications.

4. Discussion

Mathematical morphology is a usuful tool for detecting microcalcifications in digital mammograms. We proposed some new features for the detection of microcalcifications on mammograms. The basic idea is to evaluate the dynamics of microcalcifications, since each calcification appears as an elevation if we represent each mammogram as a topographic map. Digitized mammograms are very complex images with many regional maxima and minima. The main problem is the detection of clusters with two or three calcifications, especially when all of them have low intensity values and low contrast. At the moment we are investigating new methods based on mathematical morphology, in order to increase the sensitivity of our algorithm for clusters containing microcalcifications with very low intensity values.

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