DETECTION OF MASSES IN MAMMOGRAMS USING ENHANCED MULTILEVEL-THRESHOLDING SEGMENTATION AND REGION SELECTION BASED ON RANK

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ABSTRACT
A method for detection of masses in mammograms is presented. This method follows the general scheme of: (1) preprocessing of the image to increase the signal-to-noise ratio of the lesions being detected, (2) segmentation of all potential lesions, and (3) elimination of false-positive findings. An algorithm for enhancement of mammograms is proposed; this algorithm has the objective of improving the segmentation of distinct structures in mammograms, using wavelet decomposition and reconstruction, morphological operations, and local scaling. After preprocessing, the segmentation of regions is performed via conversion to binary images at multiple threshold levels (multilevel-thresholding segmentation), and a set of features is computed from each of the segmented regions. Finally, a ranking system based on the features computed is employed to select the regions representing abnormalities. The method was tested on 57 mammographic images of masses from the mini-MIAS database, including circumscribed, spiculated, and ill-defined masses. In this test, the proposed method achieved a sensitivity of 80% at 2.3 false-positives (FPs) per image.

KEY WORDS
Medical Image Processing, Breast Cancer, Breast Masses, Mammography, Tumor Detection.

1 Introduction
Breast cancer is the most common form of cancer in the female population, affecting one in approximately eleven women at some stage of their life in the Western world [1], [2]. As with any form of cancer, early detection of breast cancer is one of the most important factors affecting the possibility of recovery from the disease. Early detection of breast cancer can be achieved through mammography screening programs assisted by computers [3]. Over the past one and a half decades, several researchers have studied and proposed methods for computer-aided detection and classification of abnormalities related to breast cancer in mammograms. A brief review of the methods that are more relevant to this study is provided below.

Kegelmeyer et al. [4] investigated the use of a computer vision method as a second reader for the detection of spiculated lesions on screening mammograms. Their study included 36 positive cases and 49 negative cases. Their method achieved 97% per-image sensitivity with an average of 0.28 FPs per image.

Polakowski et al. [5] presented a model-based vision algorithm to detect and classify masses in digitized mammograms. Polakowski et al. tested their algorithm on a database containing 272 images, and reported a sensitivity of 92% in locating malignant ROIs, with an average of 1.8 FPs per image.

Kobatake et al. [6] proposed a method for the detection of malignant tumors in digital mammograms. In this method, the mammograms are first filtered with a special filter called the iris filter. Then regions for which the output of the iris filter is the highest are selected as ROIs. The performance of this method was 90.4% detection success with an average of 1.3 FPs per image when tested over 1,212 images.

Christoyianni et al. [7] presented a method for fast detection of circumscribed masses in mammograms. Their method performs classification of mammographic regions into tumorous and healthy tissue via a radial basis function neural network. They reported results of recognition of abnormal tissue of 90.9%, 62.5%, and 33.3% in fatty, glandular, and dense tissue, respectively.

Mudigonda et al. [8] presented a mass detection method that performs segmentation of objects based on isoointensity contours and texture flow-field analysis. Their study included 43 masses and 13 normal cases from the Mini-MIAS database [9]. The performance of their method was reported as 81% of detection success with an average of 2.2 FPs per image.

Zheng and Chan [10], proposed a segmentation method using the discrete wavelet transform and a multi-resolution Markov random field as part of their detection algorithm, and used a binary decision algorithm to select suspicious areas based on features from the segmented regions. Their study included 322 mammograms from the...
MIAS database with 37 masses. The sensitivity of their algorithm was reported to be 97.3% with an average of 3.92 FPs per image.

A density-weighted adaptive contrast enhancement (DWCE) filter was presented by Petrick et al. [11], [12] as part of a mass-detection algorithm including Laplacian-of-Gaussian edge detection and morphological feature classification. Petrick et al. tested this algorithm on a dataset including 175 malignant masses and 149 benign masses. The reported detection rate was 77.47%, at an average of 1.5 marks per mammogram.

In this paper, our interest is focused on the detection of masses, either benign or malignant, and including well-defined circumscribed, spiculated, and ill-defined masses. A method for the detection of masses in mammograms is proposed. This method is divided into three main stages. The first stage is a preprocessing step that has the objective of improving the segmentation of the distinct structures in the mammogram when performed via simple conversion to binary images at multiple threshold levels. Our enhancement algorithm is different from others in the literature in that it incorporates morphological, wavelet, and histogram-based operations to process the images. After enhancement and segmentation, several shape and gray-level characteristics of the segmented regions are computed, and a ranking system is employed to select suspicious regions. The ranking system is a novel approach to the problem of region selection (i.e., the elimination of FPs) that does not require training, and implements a type of on-the-fly feature selection.

2 Materials

The database of mammograms used in this study is known as MIAS (Mammographic Image Analysis Society) Mini Mammographic Database [9]. In the Mini-MIAS database, the MIAS Database (an earlier version digitized at 50 µm pixel size) has been downsampled to 200 µm pixel size and clipped/padded so that every image is of size 1024 × 1024 pixels.

The complete method presented in this paper was implemented in MATLAB [13] version 7, and makes extensive use of the Image Processing Toolbox (version 5.2). Functions involving wavelets were implemented with code from Chapter 7 of Gonzalez et al. [14]. Some of the functions for computation of shape properties were taken from Chapter 7 of Nixon and Aguado [15]. The functions used to shift the images are part of the TEMPLAR Software Package [16].

3 Methodology for mass detection

The methodology used consists of three main steps. In the first step the images are enhanced to make all structures equally detectable (or approximately equally detectable). In the second step, the enhanced images are segmented into distinct regions through thresholding at multiple levels, and a number of features are computed from each one of the regions present at each segmentation level. The third step is the selection of suspicious regions based on their features and employing a ranking system. Each of these stages is described in detail below. The region representing the pectoral muscle was manually removed from all the images previous to any further processing because it can affect negatively the results of image processing methods (see for example [8]).

3.1 Mammogram enhancement

One of the difficulties that has to be overcome for a successful detection of masses in mammograms is caused by the difference in brightness of the objects in the mammograms. Depending on the detection algorithm, this effect may increase the difficulty of detecting masses that are located near the breast boundary. Furthermore, when the density of the parenchyma is high, masses with a lower density appear with low negative contrast in the mammograms. Often such masses are missed by algorithms that use the brightness level of the structures as their main feature for detection. Other factors that increase the difficulty of obtaining a successful detection are a low signal-to-noise ratio at the edges of masses and complex structures in the background of the mammogram.

In order to alleviate the situations described above an image enhancement procedure is proposed. The objective of this procedure is to increase the contrast between mammographic structures and their background while providing a relatively uniform intensity to all of the structures. Wavelet decomposition and reconstruction [17] with Haar wavelets [18] is used in combination with the top-hat [14]
Table 1. Possible cases for block processing and subroutine employed

<table>
<thead>
<tr>
<th>Value of $k$</th>
<th>Shift direction</th>
<th>Subroutine</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>vertical</td>
<td>A</td>
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<tr>
<td>3</td>
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<td>B</td>
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<td>10</td>
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<td>10</td>
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operation to differentiate background from candidate structures; then, an averaged local scaling procedure is used to increase the contrast of the objects. In cases where the density of the objects is very high and relatively uniform, the algorithm attempts to enhance only the edges of the objects while preserving the brightness levels within the objects. Below, the complete procedure is described in detail:

First, the images are filtered with a Gaussian smoothing filter (parameters $\mu = 15$ pixels, $\sigma = 5$ pixels). Secondly, the top-hat operation is applied using a disk with radius equal to $r_{top}$ pixels as the structuring element. In the next step, the output of the top-hat operation is decomposed in three scales using wavelet decomposition, and the detail components of the first and third scales are eliminated. Following this, the image is reconstructed to its original scale without the eliminated components and then processed as shown in Figure 2 with the parameters: $k = 3, 5,$ and 10; and $j = 1$ to 9 in steps of 1 (Table 1 indicates which of the block processing routines shown in Figure 3 is employed). Finally, the maximum value between the images processed with $k = 3, 5$ and 10 is chosen for each pixel.

Figures 1 and 4 illustrate the effect of the enhancement routine on case number mdb019. Figure 1 shows the original mammogram and Figure 4 represents the enhanced version. It can be observed that all structures at different scales are easily distinguishable; in particular, the structures close to the breast boundary appear much clearer than in the original mammogram.

The value of the radius $r_{top}$ used in the top-hat operation was fixed to 80 pixels for most mammograms and 55 pixels for mammograms which are very dense and homogeneous. In our test dataset, only three mammograms show extremely dense and homogeneous tissue (cases mdb179, mdb244 and mdb315).

3.2 Segmentation and feature extraction

The enhanced images are converted to binary images through thresholding at different values starting from the top level. This segmentation technique has been used previously by Mudigonda et al. [8]. It was found that for the enhanced images in this study, with gray values in the range $[0, 1]$, 30 levels with a step size of 0.025 were adequate to segment all the mammograms.

Once the segmentation procedure described above is completed, the binary images are filtered with a Gaussian smoothing filter (parameters $\mu = 9$ pixels and $\sigma = 5$ pixels) to eliminate noise (any isolated pixels) and split regions that are joined by single pixels or by a small group of pixels. All regions with a pixel count of less than 150 pixels are eliminated because they are well below the size of the smallest mass in the Mini-MIAS database and it is unnecessary to process them. Figure 5 illustrates the set of regions extracted from the mammogram in Figure 4.

To complete this stage of the detection method, a set of properties of the remaining regions are computed and stored together with the binary image containing all regions at the corresponding segmentation level. The properties obtained from each region are: 1. area, 2. perimeter, 3. major axis length, 4. minor axis length, 5. eccentricity, 6. orientation, 7. equivalent diameter, 8. solidity, 9. extent, 10. compactness, 11. dispersion-I, 12. dispersion-II (a variation), 13. mean gradient within region, 14. mean gradient of boundary, 15. gray value variance, 16. edge distance Variance, 17. mean Intensity difference, and 18. fractal dimension. All of these measures were computed using the gradient and intensity values of the enhanced mammogram except for the Fractal Dimension, which was computed using an adaptation of the method of Caldwell et al. [19],
Figure 3. Block processing subroutines. The threshold in Subroutine A was set to 0.6 for images with pixel values in the range [0, 1].

Figure 4. Enhanced mammogram.

Figure 5. Contours of regions segmented at multiple threshold levels.

Figure 6. The concept of a scoring area: if the absolute value of the difference between property \( j \) of a region and the mean of property \( j \) over all masses is inside the scoring zone, the region receives a score of 1.

from the original mammogram.

### 3.3 Selection of suspicious regions

The selection of suspicious regions is performed by means of a ranking system. The ranking system used in this study is based on the assumption that even when not all the properties of a suspicious region will be concentrated around a certain value and within a fixed range, most of them will be so concentrated. By considering how many of the properties of each given region are concentrated around a reference value and within a fixed range (let this be called the scoring zone), a rank can be assigned to each region. The reference value for each property is the mean value of that property computed over the set of masses, and is located at the center of the scoring zone. The range defining the extent of the scoring zone is the standard deviation of the property (again, computed over the set of masses) times a regularization factor \( \alpha \); this is illustrated in Figure 6. The reference means and standard deviations were obtained using the ground truth of the masses in the Mini-MIAS database as a guide.

To compute the rank of the \( i \)-th region, the absolute value of the difference between the set of properties \( \bar{x}_i \) and
the set of means $\bar{\mu}$ is compared against the limit of the scoring zone, $\alpha \bar{\sigma}$, where $\bar{\sigma}$ is the set of standard deviations. A score of 1 is given to the region for each difference that is lower or equal to the corresponding limit, and zero for each difference that is larger than the limit. The scores are stored in a vector of 1s and 0s, $\bar{Z}$, that works like a scoring card: the vector shows how many and which properties of each region are inside the scoring zone.

The rank of the $i$-th region is mathematically expressed as

$$\bar{Z}_i = \| \bar{x}_i - \bar{\mu} \| \leq \alpha \bar{\sigma},$$

$$rank_i = \| \bar{Z}_i / \bar{\sigma} \|,$$

where we use $\|$ to clarify that $\bar{Z}_i$ receives the outcome of the test condition $\| \bar{x}_i - \bar{\mu} \| \leq \alpha \bar{\sigma}$, which is 1 if the condition is true and zero otherwise.

The value of the parameter $\alpha$ for the ranking system described above was chosen empirically, and fixed to 1.9 for all experiments. Once the ranks of all regions are computed, the algorithm selects the ones with high ranks up to a desired number of regions. Note that the choice of the number of regions that are to be returned by the algorithm does not affect the processing time, because the ranks of all the regions must be processed before any number of them is selected.

4 Results and Discussion

4.1 Results

The algorithm for mass detection was tested on a set of 57 mammograms from the Mini-MIAS database including circumscribed, spiculated and ill-defined masses. A true positive (TP) was recorded for a segmented region when the region overlapped the centroid of a mass, represented by a circular area with a radius of five pixels. Otherwise, the region was considered as FP. A similar definition of a true positive (TP) was used by Mudigonda et al. [8] and part of the method of Petrick et al. [11].

The algorithm was tested with four sets of properties to test their discrimination power. One set included all the properties, whereas the other three included a subset of these. Subset $A$ included all properties except the very basic shape descriptors (i.e., properties 7 to 18). Subset $B$ included only the measures corresponding to gray-level characteristics (properties 13 to 18). Subset $C$ included only the more advanced shape descriptors (properties 7 to 12).

Figure 7 presents a plot of the true positive (TP) fraction vs false positives (FPs) per image.

The clear advantage is that the initial sensitivity is high; other advantages are that the design of the algorithm is simple and the implementation does not require complex computations. The most time-consuming operation is the computation of the properties of all the regions segmented. The time used in this operation can be reduced by either reducing the initial number of regions or the number of properties used.

4.2 Discussion

The detection of masses used in this study follows the general scheme of first finding all possible distinguishable regions, and then sorting out which of them actually represent masses in the mammograms. This scheme has the disadvantage that a very large number of regions must be processed, which is costly in computing time and resources. The clear advantage is that the initial sensitivity is high; other advantages are that the design of the algorithm is simple and the implementation does not require complex computations. The most time-consuming operation is the computation of the properties of all the regions segmented. The time used in this operation can be reduced by either reducing the initial number of regions or the number of properties used.

The ranking system used in this study works at two levels simultaneously: the scoring system itself works at a general level; it is a rough or fuzzy way to determine the best candidates (that is, the most suspicious regions). The scaling of the scoring vector by the vector of standard deviations is a compensation step that works at a second and finer level. The ranking system, as a whole, then performs a type of on-the-fly feature selection for each one of the images processed. Kobatake et al. [6] used a method similar to our ranking system to select malignant masses. Their method computes the Mahalanobis distance measure between an input vector $\bar{x}$ and the mean vector of two categories (1: malignant mass and 2: others), $D_1$ and $D_2$. Our method is different, in that it uses data from only one category instead of two; we assume a diagonal covariance matrix, and include an intermediate step that converts the distances to binary values.
5 Conclusion and Future Work

A computer-aided method for the detection of masses in mammograms has been presented. With a performance of 80% of all types of masses in the test database being successfully detected at 2.3 FPs per image, this algorithm is comparable to other methods in the literature. Combining this algorithm with other detection methods, refining the system for FP reduction, and including a feature selection step are being considered for future work.

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References


