A Supervised Method for Microcalcifications Detection using Breast Density

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Abstract

The increasing mortality rate due to breast cancer is a global concern. Several research groups have proposed different methods to detect breast cancer in an early stage (such as microcalcifications detection methods). In this work, we present a supervised microcalcifications detection method that takes into account the breast density. Using this information and Fisher´s Linear Discriminant, our method is able to detect microcalcifications even in mammograms where there is not contrast between microcalcifications and breast tissue. We tested our method with two mammogram databases and we evaluated each of the main phases of the method. The obtained specificity and sensitivity results reached 90% for each of the phases.

Keywords: microcalcifications detection, breast density, segmentation, data mining.

1. Introduction

Breast cancer is the most common cause of death among women. The American Cancer Society estimates that each year in the United States, 40,170 women die from breast cancer.

Although there are risk factors associated with breast cancer, no woman is safe from this disease. For this reason, physicians recommend periodical clinical revisions (such as mammograms) to detect its presence in an early stage.

Microcalcifications are the symptom that tells us with more anticipation the probable beginning of a malignant process inside the breast (breast cancer). They can be observed in mammograms and they look like little bright points of different tones, shapes, and sizes.

For twenty years, several research groups have proposed different automatic methods to segment microcalcifications. These methods can be divided, depending on the segmentation technique used, in four categories: thresholds (Mousa et al. 2005, Wang et al. 1998, Wu et al. 2006), regions (Kim and Park 1997, Morrow et al. 1992, Woods et al. 1997), model or supervised segmentation (Nishikawa et al. 2002, Perner 1999, Zhang et al. 1998) and contours based methods (Fu et al. 2005, Lee et al. 2004, Zhao et al. 1992).

The thresholds based methods are the most popular. Most of these methods use a wavelet transformation to highlight microcalcifications to then apply a threshold. These methods only work well when there is a high contrast between microcalcifications and the surrounding region (breast tissue).

There are also region based methods that look for some distinctive value of the pixels that form a microcalcification. However, finding this value is very difficult due to the different tones between microcalcifications and the different types of breast tissue (fat and glandular).

Other methods use information about the objects to be segmented; this segmentation technique is known as supervised segmentation or model based segmentation. This technique is used when the objects to segment have a geometric pattern as we can see in the case of microcalcifications. The main problem of these methods is the strong dependency between the identification results and the images used to learn the model (even more when such a model is based on the image tonalities).

Finally, there are methods that try to detect the borders of microcalcifications. These methods are not commonly used because finding those borders is difficult when there is a low contrast between microcalcifications and the breast tissue.

As we could notice, all the methods described before have a common problem: the detection results depend on the contrast between microcalcifications and their surrounding region (the breast tissue). The tone difference in a mammogram is caused by the type of tissue (fat or

glandular) that composes the majority of the breast. For this reason, we proposed a detection method that takes into account the breast density (the predominant breast tissue). Using this information and Fisher´s Linear Discriminant, our method is able to detect microcalcifications of any tone, size, and shape. In the last phase of our method, we extract descriptive characteristics from the detected microcalcifications to reduce the number of false positives.

In section 2 we describe how Fisher´s Linear Discriminant works and in section 3 we describe the proposed method to detect microcalcifications. The mammogram databases that we used to test our method are shown in section 4 and in section 5 we present our results. Finally, in section 6 we show our conclusions.

2. Fisher's Linear Discriminant

The main idea of Fisher´s Linear Discriminant (FLD) is to find a space where the projected samples from different classes are well separated. In other words, this method selects the projection U such that the ratio of the average between-class scatter over the average within-class scatter is maximal.

Let the between-class scatter matrix be defined as

$$S_b = \sum_{i=1}^{k} N_i (\mu_i - \mu)(\mu_i - \mu)^T \quad (1)$$

and the within-class scatter defined as

$$S_w = \sum_{i=1}^{k} \sum_{j=1}^{N_i} (x_j - \mu_i)(x_j - \mu_i)^T \quad (2)$$

where μ is the general mean

$$\mu = \frac{1}{N} \sum_{j=1}^{N} x_j \quad (3)$$

and μ_i is the mean of class *i* which is defined by

$$\mu_i = \frac{1}{N_i} \sum_{j=1}^{N_i} x_j \quad (4)$$

If S_w is a non-singular matrix, the optimum linear transformation *U* corresponds to the *m* eigenvectors with higher eigenvalues of $(S_w^{-1})(S_b)$.

$$U_{opt} = \arg\max_{U} \frac{|U^T \cdot S_b \cdot U|}{|U^T \cdot S_w \cdot U|} \quad (5)$$

Once the optimum linear transformation is found, the examples are projected into this new space.

In order to classify a new object, it is projected to the discriminant space and we calculate Euclidean distance from this new object to each of the means of the different classes. The class assigned to the new object is the one with the closest distance to it. In the next section we describe how we use Fisher´s Linear Discriminant to detect microcalcifications.

3. Microcalcifications Detection Method

Our detection method (see figure 1) is composed by three main phases: breast density classification, microcalcifications segmentation, and the phase to reduce the number of false positives generated in segmentation phase.

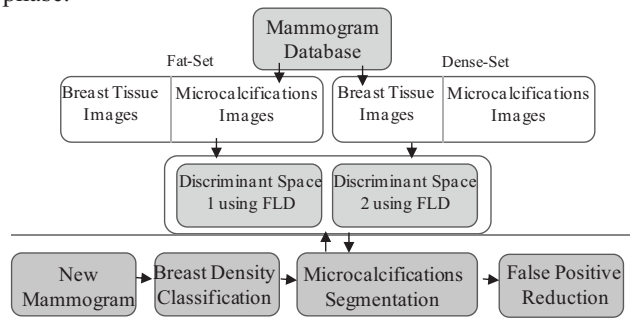

Figure 1. *Structure of the proposed detection method.*

In the first phase, the method identifies the breast predominant tissue and classifies it as either fat or dense. Then, using this information (the breast density), the method selects the discriminant space that better differentiates between microcalcifications and breast tissue.

The next step is the microcalcifications segmentation. In this phase, the breast is analyzed using a fixed size window; the image inside the window is projected into the selected discriminant space and we classify the image as microcalcification or breast tissue. If the image is identified as microcalcification, this area is marked in the mammogram indicating the presence of a possible microcalcification. This procedure is repeated until the entire breast image has been analyzed.

In the last phase, we reduce the amount of false positives generated in the segmentation step. To do this, we extract different descriptive characteristics from the regions identified as microcalcifications and we use a classification algorithm. In the next subsections we describe in more detail each of the main phases of the method.

3.1. Breast Density Classification

The type of tissue that mainly composes the breast is important for us because the contrast between the microcalcification and the breast tissue depends on it.

The breast density phase (see pseudo code 1) begins with the separation of the breast and the mammogram background (line 3 of pseudo code 1) using the fuzzy c-means algorithm (Bezdek 1981). If we only consider two groups, one of them contains all those pixels that belong to the breast and the other those pixels that are part of the background of the mammogram. The image is divided into sub-regions and we only keep the largest one (corresponding to the breast). Small regions (corresponding to labels with patient information) are eliminated.

Because the image tone is the main radiological characteristic that differentiates fat from glandular tissue, we use attributes from the breast histogram in order to identify which is the predominant tissue (tone) of the breast (line 4 of pseudo code 1). The breast image histogram is divided in seven static intervals and for each of them we obtain its mean, frequency, and standard deviation (line 5 of pseudo code 1). All of the frequency values were obtained in proportion to the breast size. The mean value tells us the average level of luminosity in the interval, frequency is the number of pixels inside the color interval, and the standard deviation corresponds to the difference in contrast inside the interval. We selected these attributes because we experimentally identified that they provide us significant information for our task.

Using the extracted characteristics and a classification algorithm our method identifies the breast category (fat or dense) (line 6 of pseudo code 1).

Pseudo code 1. *Breast Density Classification*

1. Breast_Density (New Mammogram)
2. Mammo New Mammogram;
3. Breast Fuzzy cmeans (Mammo, 2);
4. Hist histogram (Breast);
5. Intervals divided (Hist);
6. Characteristics extract characteristics (Intervals);
7. Density classifier (Characteristics);
8. Return Density;

3.2. Microcalcifications Segmentation using FLD

The second phase of our method consists of the microcalcifications segmentation. In the training step of this phase, we use Fisher´s Linear Discriminant (FLD) to create two discriminant spaces that allow us differentiate between a microcalcification image and a breast tissue image. In order to generate the discriminant spaces, we create two microcalcifications databases. Both of them contain microcalcifications images and breast tissue images, but one database has images from fat breasts and the other has images from dense breasts. The images of the microcalcifications database are stored in jpg format and they have a size of 12 x 12 pixels.

The procedure to find a discriminant space using FLD (see pseudo code 2), begins with a set of N images with the same size; where N_c images belong to the microcalcification class and N_b images belong to the breast tissue class. After that, each image is represented as a column vector (in our case a vector of 144 pixels), line 2 of pseudo code 2. Using these vectors, we calculated the general mean and the mean of each class (see equations 3 and 4), lines 3-5 of pseudo code 2.

Then, we calculate the between-class scatter matrix S_b and the within-class scatter matrix S_w (see equations 1 and 2), lines 10-11 of pseudo code 2. In order to find the linear transformation matrix U, we obtain the eigenvectors of the product of S_b and S_w^{-1}(see equation 5), line 14 of pseudo code 2. If we directly apply FLD to our images, we fall into a problem; the inter-class dispersion matrix S_w is always singular. This happens because the number of pixels n is higher than the number of images M, and the maximum range of S_w is (M-k), so S_w is always singular. In order to solve this problem, the space is reduced using Principal Component Analysis (PCA) before applying FLD (Belhumeur et al. 1997), lines 7-8 of pseudo code 2. After this, the optimum linear transformation U consists of the eigenvectors of $(U^T{}_{PCA} S_w U_{PCA})^{-1}(U^T{}_{PCA} S_b U_{PCA})$.

This procedure to create a discriminant space is repeated twice, the first one using the database with images from fat breasts and the second one using the database with images from dense breasts.

Pseudo code 2. *Microcalcifications discriminant space*

1.Microcalcifications Discriminant Space(image base)
// The image base contains images of microcalcifications and images of breast tissue.
2. Transform each image into a vector X_i ;
3. Mean general mean (X_1,...,X_m);
4. Mean calc mean (images of class 1);
5. Mean tissue mean (images of class 2);
6. matrix [X_1,..,X_m];
7. M matrix^T * matrix;
8. [eigevectors,eigenvalues] eigenvectors(M); // Mv λv
9. V matrix * eigenvectors;
10.S_B calculate_Sb (Mean_general, Mean_calc, Mean_tissue);
11.S_W calculate_Sw (Mean_calc, Mean_tissue);
12.S_b $V^T * S_B * V$;
13.S_w $V^T * S_W * V$;
14.[Eigenvec, Eigenval] eigenvectors(S_b,S_w); // $S_b v$ $S_w \lambda v$
15.U V * Eigenvec;
16.Project all images in U; //(Y_i $U^T * X_i$)ioi
17.Mean class calc mean (images class 1);
18.Mean class tissue mean (images class 2);
19.Save U, Mean class calc, Mean class tissue;

Once the two discriminant spaces were generated, in the microcalcifications segmentation step (see pseudo code 3), we use a window of 12 x 12 pixels to analyze the breast to look for microcalcifications (line 4 of pseudo code 3). The region inside the window is projected to the corresponding discriminant space (line 7 of pseudo code 3) depending on the breast density classification. Then, using the Euclidian distance we identify if there is more similarity between the image and the microcalcifications or the breast tissue class (line 8 of pseudo code 3). If the region inside the window is classified as microcalcification (lines 9-10 of pseudo code 3), this area is marked in the mammogram; otherwise, we only move the window. The segmentation step finishes when the window has analyzed the whole breast.

3.3. False Positives Reduction

The false positives reduction is the last phase of our method. In this phase we extract descriptive characteristics including statistical (i.e. minimum and maximum gray levels) and morphological (i.e. area, perimeter, convex area, orientation, minor axe length, major axe length, and solidity) from the microcalcifications segmented in the segmentation step.

Pseudo code 3. *Microcalcifications detection using FLD*

```
1. Detection using FLD (New Mammography Image)
2. Density   Breast Density (Mammo);
3. Load U, Mean class calc, Mean class tissue corresponding to
   Density;
4. For each no overlapping window from top left to bottom rigth
5.  Region   window (Mammo);
6.  VRegion   vector column (Region);
7. NewIm   U^T * VRegion;
8. Dist Min Euclid (NewIm, Mean_class_calc, Mean_class_tissue)
9.   if (Dist    Mean class calc)
10.     Highlight (Region);
11.end for
```

Since we used a sliding window during the segmentation phase, the segmented microcalcifications contain a small region of breast tissue. Due to this, we need to segment the region of interest using the Otsu method in order to calculate its descriptive characteristics (Otsu 1979). Using these characteristics and a classifier we reduce the amount of false positives.

4. MIAS and SSSIESSP Databases

In this work we used two mammogram databases, the mini-MIAS and the SSSIESSP databases. The mini *Mammographic Image Analysis Society* (MIAS) is a public database that contains 322 images of medium lateral mammograms (Suckling et al. 1994). The MIAS database has an information document associated to each mammogram that describes its characteristics such as: breast density, the anomaly found in the mammogram, the anomaly malignity, the coordinates of the center of the anomaly and the approximate radius in pixels of the circle that encloses the anomaly. The size of each image is of 1024 x 1024 pixels and the images are stored in pgm format.

The second database that we used is known as the SSSIESSP database. This database was created with mammograms from the X-rays laboratory of the Social Services and Security Institute of Employees to the Service of the State of Puebla (SSSIESSP). This database has 84 cases, each case has 4 mammograms: 2 medium lateral angle mammograms (right and left) and 2 cranium-caudal mammograms (right and left). These mammograms were digitized with a special scanner for negatives (Epson Expression 1680 Professional Firewire) with a resolution of 1600 dpi. The size of the images is of 1024 x 1024 pixels and the images are stored in the jpg format.

With the help of a domain expert (a radiologist), the mammograms were analyzed and the anomalies were classified.

5. Results and Discussion

We tested our method with the MIAS and the SSSIESSP databases described in section 4. Each of the main phases of the method was evaluated in order to measure its performance. The following subsections describe the experiments performed and the obtained results.

5.1. Breast Density Classification Results

For the evaluation of this phase we used mammograms with and without microcalcifications. We used as our learning set 150 mammograms from the MIAS and 145 from the SSSIESSP databases. We tested three learning algorithms: a rule based classifier (PART), a neural network (MultiLayer Perceptron), and an instance based classifier (IB1). As evaluation measures we used the sensitivity (true positives rate) and specificity (true negatives rate) generated by each classifier. In this phase of our method, the positive class corresponds to the fat class and the negative class to the dense class. Table 1 shows the results obtained in these experiments to classify the breast density for each of the mammograms database.

For both mammograms databases the classification results for the fat class (sensitivity value) was lower than that of the dense class (specificity). This happened because some fat breast mammograms contain a large area of the pectoral muscle and the classifier erroneously cataloged them as dense mammograms.

Table 1. *Results of breast density classification.*

Mammograms with microcalcifications				
Classifiers	MIAS Database		SSSIESSP Database	
	Sensitivity	Specificity	Sensitivity	Specificity
MLPerceptron	0.8	0.93	0.84	0.91
PART	1	1	0.75	0.87
IB1	0.8	0.93	0.88	0.91
Mammograms without microcalcifications				
MLPerceptron	0.85	0.93	0.83	0.95
PART	1	0.93	0.83	0.91
IB1	0.9	0.9	0.91	0.95

5.2. Microcalcifications Segmentation Results

In this experiment we only used mammograms that contained microcalcifications (20 from the MIAS and 50 from the SSSIESSP database). We tested our method with and without considering the breast density knowledge obtained in the previous phase. The performance evaluation was done with the FROC analysis, using as evaluation measures the proportion of true positive marks

(TPR) and the proportion of false positive marks per image (FPI).

A true positive mark corresponds to the location of a microcalcification detected by the segmentation algorithm, while a false positive mark corresponds to the location of breast tissue that was erroneously classified as a microcalcification by the segmentation algorithm. In figure 2 we show examples of microcalcifications regions detected in some mammograms. Table 2 shows the results obtained in the microcalcifications segmentation phase.

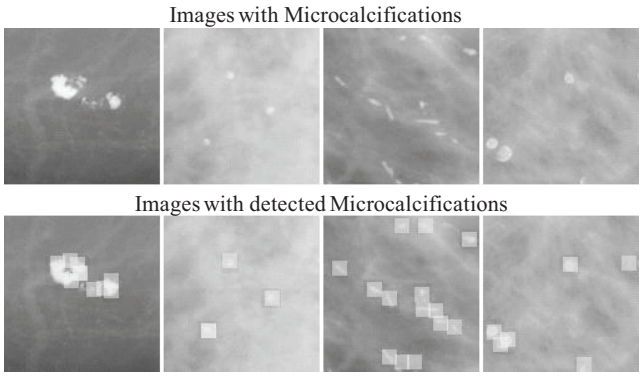

Figure2. *Examples of breast regions where microcalcifications were detected.*

Table 2. *Results of the segmentation phase showing the TPR and FPI measures for the MIAS and SSSIESSP databases.*

Microcalcifications Detection Phase								
	MIAS Database				SSSIESSP Database			
	Fat Breast		Dense Breast		Fat Breast		Dense Breast	
	TPR	FPI	TPR	FPI	TPR	FPI	TPR	FPI
Using FLD and breast density	**91.8**	**1**	**90.9**	**4**	**94.3**	**6.1**	**92**	**7.4**
Using FLD without breast density	88.9	18	70	21	65.1	2.3	83	5.3

It is important to note that the TPR obtained with our method was higher than 90% for both databases, even with difficult breasts (dense breasts). Our method obtained a TPR 10% higher than when we do not take into account the breast density. Moreover, we can see that taking into account the breast density, our method generated a lower false positives rate.

5.3. False Positive Reduction Results

The evaluation of this phase was also performed using mammograms with and without microcalcifications. We used 3 classifiers: a neuronal network (Multi Layer Perceptron), an instance based classifier (IB1) and a rule based method (PART). We used sensitivity and specificity as evaluation measures. Table 3 shows the results obtained in this test. In the false positives reduction phase the method showed a good performance. Using mammograms with microcalcifications the true positive rate (sensitivity) and the true negative rate (specificity) were around 0.9. While for mammograms without microcalcifications the true negative rate was 0.92. We write NA in some sensitivity results of table 3 because a sensitivity value is not applicable to mammograms without microcalcifications.

Finally, table 4 shows the results of the global performance of the proposed method.

Table 3. *False Positive Reduction showing Sensitivity and Specificity results.*

False Positive Reduction Phase						
MIAS Database						
	MLPerceptron		PART		IB1	
	Sens	Spec	Sens	Spec	Sens	Spec
Mammograms with microcalcifications	.85	.99	.94	.98	.87	.98
Mammograms without microcalcifications	NA	.99	NA	.87	NA	.95
SSSIESSP Database						
Mammograms with microcalcifications	1	.99	.90	.99	.90	.98
Mammograms without microcalcifications	NA	.92	NA	.88	NA	.92

Table 4. *Results of the global performance.*

Global Performance of the Proposed Method		
	Sensitivity	Specificity
MIAS Database	0.88	0.90
SSSIESSP Database	0.9	0.90

The average of the microcalcifications detection rate per mammogram was around 0.9 while the average of false positives rate per image was of 0.1.

6. Conclusions

In this work we presented a method to detect microcalcifications based on Fisher's Linear Discriminant that considers information about the breast density for the segmentation step and allows reducing the amount of false positives generated during the segmentation phase. Experimental results were satisfactory in each phase, showing performances over 90%. It is important to notice that our method is able to identify very bright and opaque microcalcifications, even in very dark mammograms without the need of preprocessing the image. We can also notice that the use of knowledge about the breast density in our method increases the microcalcifications detection rate in more than 10%, allowing their identification in dense breasts (known to be difficult for this task) without incrementing the amount of false positives generated.

As future work, we will improve the breast density classification phase to identify which regions of the breast

corresponds to fat tissue and which others correspond to glandular tissue. In this way we can improve our method to use the two discriminant spaces in an adaptable way.

We will also develop a diagnosis phase that considers features such as shape, number, and location of the microcalcifications in order to identify their malignancy level.

On the other hand, when we analyzed the literature for this work, we could see that some works only present the result of the false positives reduction (the classification step) but it is also important to consider that the number of microcalcifications that the false positives reduction phase processes depends on the number of microcalcifications identified in the segmentation phase, then, the performance of the false positives reduction phase is affected by the cumulative error carried from the segmentation phase. For this reason we propose to generate a new evaluation scheme for microcalcifications detection methods, in which we can evaluate all of the method phases in a fair way and then obtain their global performance.

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