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Mammographic Images Segmentation using Texture Descriptors

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Abstract— **Tissue classification in mammography can help the diagnosis of breast cancer by separating healthy tissue from lesions. We present herein the use of three texture descriptors for breast tissue segmentation purposes: the Sum Histogram, the Gray Level Co-Occurrence Matrix (GLCM) and the Local Binary Pattern (LBP). A modification of the LBP is also proposed for a better distinction of the tissues. In order to segment the image into its tissues, these descriptors are compared using a fidelity index and two clustering algorithms: *k*-Means and SOM (Self-Organizing Maps).**

I. Introduction

BREAST cancer is the most common cancer and the second cause of cancer death between women [1]. Although mammography is widely used in the diagnosis of breast cancer, the interpretation of mammograms is a difficult task and the experience of the radiologist is crucial in the process [2].

Analysis of mammographic images using computers has been accepted to help radiologists during the diagnosis [3]. Several studies have been developed in this sense and the contributions involve lesion detection, region classification (such as tumors or calcifications), and query of similar cases within a database. Texture analysis is an interesting issue for these systems as it performs an evaluation close to what is done by the human visual system.

Bovis and Singh [4] proposed a classifying system to detect masses in mammograms on the basis of textural features using a comparison between both breasts of the woman.

Santo et al [5] presented a multiple classifier scheme to combine classification of calcifications independently with classification of clusters of calcifications as a whole. The system performs an analysis based on features such as shape and texture to provide the classification as benign or malign clustered calcifications.

Zheng et al [3] constructed a system to retrieve similar images of lesions in mammography. The system classifies the boundary shape and a set of features are extracted to represent the lesion and its surrounding tissue background.

Textural attributes can provide a description of breast tissue and this can be helpful to distinguish between lesions and healthy tissue.

Texture can also be used for segmentation as is proposed by Arivazhagan and Ganesan [6,7] where it is presented a segmentation scheme based on combination of co-occurrence features and wavelet statistical features.

In this paper, we present the use of three texture descriptors for segmentation of the breast tissue: the Sum Histogram, the Gray Level Co-Occurrence Matrix (GLCM) and the Local Binary Pattern (LBP). It is proposed a combination of these descriptors with a fidelity index to provide a comparison between regions in a mammogram and segment different classes of tissues. It is also proposed a modification of LBP that improved differentiation between the tissues.

Also, we used SOM (Self-Organizing Maps) networks and *k*-Means clustering to guide the segmentation for further classification with the fidelity index and the texture descriptors.

The paper is organized as follows: Section II presents the images and techniques used in this research; Section III shows experiments with the comparison between texture descriptors using a fidelity index. The same section also presents the analysis of the use of clustering algorithms for segmenting mammographies. Section IV contains a discussion about the methods presented herein.

II. Material and Methods

For the experiments, the miniMIAS database [8] was used. It contains 322 mammographic images from left and right breast of 161 patients, some of them healthy and others containing lesions such as benign or malign tumors and calcifications. In Figure 1, it is shown samples of the database.

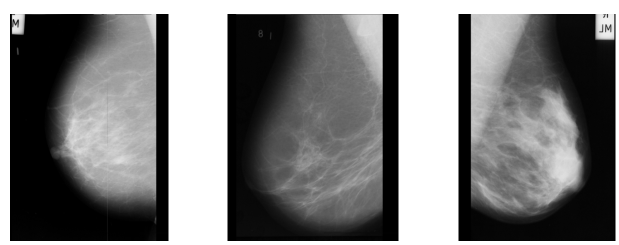

Figure 1. Three sample images from MiniMIAS mammographic database

The breasts contain a mixture of glandular and adipose tissues which are displayed in the mammography. Dense tissues (glandular) appear as bright regions and the adipose as dark regions. Since we aim to distinguish the different tissues in the mammography, the use of texture attributes is appropriated to describe them.

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A. Texture descriptors

Texture can be understood as a color pattern that varies along surfaces and helps the human visual system to identify the shape and material of the objects [9].

Texture descriptors are computational ways to represent a texture. Some of the main texture descriptors are: GLCM (Gray-Level Co-occurrence Matrix) [10], SDH (Sum and Difference Histograms) [11] and LBP (Local Binary Pattern) [12].

GLCM is a C x C matrix, where C is the color resolution of the image. For example, for a 256 gray-levels image, the GLCM is a 256 x 256 matrix. Each cell of this matrix stores a counter. The cell (i, j) presents how many times the colors *i* and *j* can be found in the image separated by a distance (*dx, dy*) which is previously defined according to the application.

The SDH works the same way as the GLCM but it stores the sum of the colors (*i, j*) and (*i+dx, j+dy*) in a histogram with 2C elements.

LBP acts with a matrix of weights (all of them are power of 2). This matrix analyses the 8 neighbors of a pixel. The result is stored in a histogram with 256 positions for a 256 gray levels image.

In Figure 2, there is an example of the use of LBP. Figure 2a represents part of an image and Figure 2b shows a binary matrix containing the comparison of each of the 8 neighbors with the central pixel in a 3x3 window. If the color of the neighbor is lower than the color of the central pixel, it becomes 0; otherwise it turns to 1. Figure 2c presents the matrix of weights of the LBP as defined in [12][12]. The values of the binary matrix are multiplied for the respective weight, generating the matrix in Figure 2d. The final result is the sum of the values of this last matrix.

a)

6	5	2
7	6	1
9	3	7

b)

1	0	0
1		0
1	0	1

c)

1	2	4
8		16
32	64	128

d)

1	0	0
8		0
32	0	128

Figure 2. Computation of LBP: a) the image, b) binary image obtained by comparison with the central pixel, c) LBP's weight matrix and d) the result of multiplying b) and c) element by element.

The problem with LBP is that it assigns high weights for some positions, giving higher weights for some neighbors of the central pixel. Also, LBP does not extract any information about the colors (gray levels) of the pixels, only from the relationship between them.

To solve the problem of unbalanced weights, we propose a modification on the LBP descriptor: we use 4 matrices of weights instead of just one, where the new matrices are rotated versions of the original (Figure 3).

The computation of LBP is done the same way as before for each one of the four matrices of weights and the value incremented in the LBP histogram is the average result of each of these evaluations. If we proceed with the sample window of Fig. 2a for each of these matrices of weights, the results are: 169, 228, 149 and 39, generating an average value of 146. Thus, the value 146 of the LBP histogram is incremented. This approach gives a better distribution of the weights along the neighbors and it still preserves the 256-position range of the histogram.

1	2	4
8		16
32	64	128

32	8	1
64		2
128	16	4

128	64	32
16		8
4	2	1

4	16	128
2		64
1	8	32

Figure 3. Modification of the LBP descriptor: rotation of the original matrix of weights to better distribute the weights.

However, there is another failure in the LBP descriptor: it looses the color information of the image. Because of this, we propose to add the average value of the 3x3 window to the value of the LBP histogram. With this second modification, the LBP histogram varies from 0 to 510. We called this descriptor as Modified LBP.

B. Texture Comparison

To segment the breast tissue we compare the texture of different regions of the mammography with a fidelity index applied to a texture descriptor.

A fidelity index evaluates the similarity between two images. Wang and Bovik [13] proposed a fidelity index with meaningful results when comparing images with some distortion as such imposed by JPEG file format losses. This index is defined as:

$$Q = \frac{4.\mu_x.\mu_y.\sigma_{xy}}{((\mu_x)^2 + (\mu_y)^2).(\sigma_x^2 + \sigma_y^2)}$$

where x and y are the original and tested images respectively; μ_x and μ_y are their average values; σ_x and σ_y are their variance and σ_{xy} is the correlation between them. The range of Q is [-1, 1] and the images are more similar as the value of Q becomes higher. When Q is equal to 1, the images are the same.

However, as defined, the index is not suitable for texture analysis [14]. Since we want to distinguish the different breast tissues, we propose to apply the index in a texture descriptor, instead of the image itself.

In order to segment and classify the breast in dense or fatty tissue, parts of the mammography image can be compared to samples previously classified and the similarity evaluated by Wang and Bovik's fidelity index. After this, these parts are assigned to the class of tissue which achieves the higher value of Q. This is presented in next section.

The process described above is used to compare parts of the same image can be used to segment and cluster similar texture regions. Hence, parts that are similar can be considered as the same texture class. This is suitable to a particular problem of segmenting the breast edge, which is a region of the breast predominantly composed of fat tissue. The use of the index with the Sum Histogram for purposes of segmenting the breast edge is presented in [14].

III. EXPERIMENTS

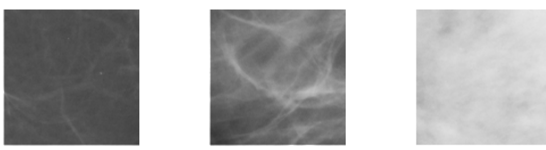
Two segmentation experiments are described herein: the first achieves segmentation using the fidelity index Q and the other experiment uses clustering algorithms. In both experiments, texture descriptors are used.

A. Segmentation with the Index Q

To segment and classify the breast tissue of a mammography we constructed a dataset with sample images of three categories of breast tissues: adipose tissue, glandular tissue and dense glandular tissue. Examples of these samples classes can be seen in Figure 4. We selected 96 images from miniMIAS database and extracted 183 samples with 120x120 pixels from these images, divided as:

- 49 samples of adipose tissue (26.78% of the total amount of samples);
- 66 samples of glandular tissue (36.06%);
- 68 samples of dense glandular tissue (37.16%).

To avoid the need of a previous step for the segmentation of the background (the film), we simply added to the database a single sample of film.



a) b) c)

Figure 4. Samples from mammograms: a) adipose tissue, b) glandular tissue and c) dense glandular tissue.

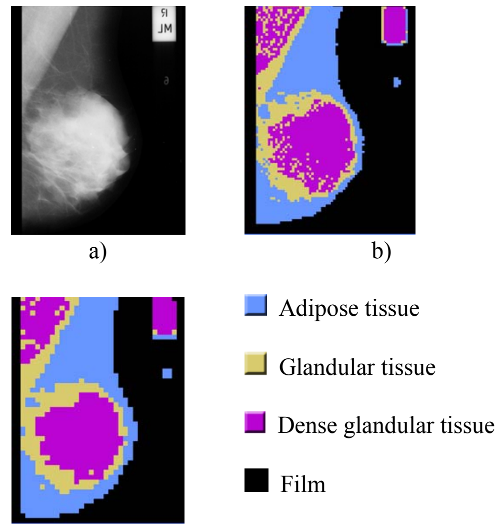
In general, it can be noted that the adipose tissue appears as a homogeneous dark region. The glandular appears as a heterogeneous region, sometimes containing fibers, and brighter than the adipose tissue. The dense glandular appears as brighten regions and it is more frequent in young patients.

To segment and classify the mammography in these three classes of tissues, the image is subdivided into regions (windows). Each window is compared using Z.Wang's fidelity index (*Q*) with all the samples of each tissue class; it is assigned to the tissue class with higher value of Q. Hence, every breast region of the mammography will be classified into one of the three tissue classes. This comparison resulted in very poor results. So, in order to improve the results, we compared the descriptors of each region instead of the image of the region.

The fidelity index Q is then applied to the GLCM, Sum Histogram, LBP and the Modified LBP. These descriptors are evaluated for each window.

Some results of using Q with the Sum Histogram and GLCM are shown in Figure 5. We can see that the results are similar. The problem of using the GLCM is that it is computationally very expensive. Figure 5b presents the use of the Sum Histogram with a window size of 10x10 pixels and a displacement dx=dy=1. Figure 5c shows the use of GLCM with a window size of 20x20 pixels and dx=dy=1.

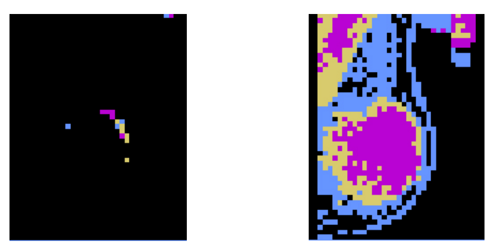
The variation in the displacements *dx* and *dy* with values 0, 1 or 2 for the Sum Histogram or the GLCM did not changed the classification of the tissues in the experiments. Also, the variation on the size of the window (10x10, 15x15 or 20x20 pixels) caused little impact on this classification, but the results with smaller windows are visually better, as shown in Figure 5.



a) b) c)

Figure 5. Segmentation and classification of breast tissues: a) original mammographic image, b) fidelity index applied to the Sum Histogram in 10x10 windows and c) fidelity index applied to the GLCM in 20x20 windows.

The use of the LBP descriptor did not present satisfactory results. In Figure 6a, it is presented the tissue classification of Figure 5a using the index Q applied to the LBP descriptor. It can be observed that almost all the image was misclassified as film (in black). However, with the proposed modification of LBP, the different tissues were identified and the classification was similar to the results obtained with Sum Histogram and GLCM (Figure 6b).



a) b)

Figure 6. Segmentation and classification using LBP: a) use of original LBP and b) use of the Modified LBP.

B. Segmentation with Clustering Algorithms

The method presented before has the problem of segmenting the image into rectangular windows, losing the contour of the objects. To avoid this, we applied two clustering algorithms: *k*-Means [15] and SOM [15] (Self-Organizing Maps).

The use of a clustering algorithm brings a pixel-to-pixel segmentation, avoiding the appearance of large blocks caused by the use of windows. The classification with the index Q combined with a texture descriptor can be used right after this previous segmentation, comparing the regions obtained with the tissue samples as before.

Some examples of segmentation obtained with these algorithms are presented in Figure 7 with variation on the number of classes desired. Here the color information just means the different clusters found; they are not related with the tissues classes. The segmentation obtained with k-Means and SOM are very similar, with no visual difference. However, *k*-Means has a lower computational cost.

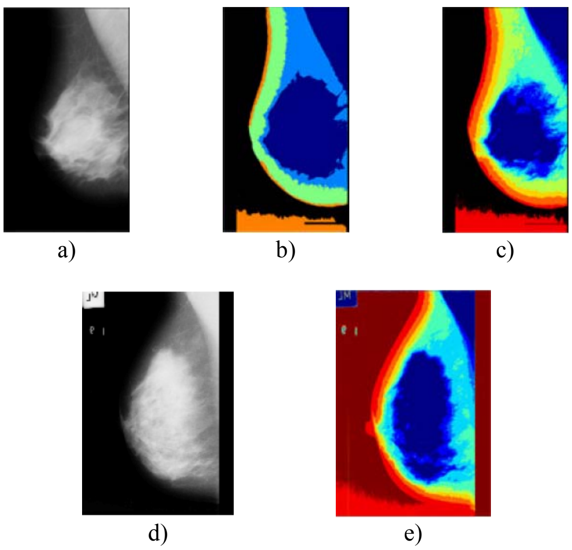


Figure 7. Use of SOM and *k*-Means for mammography segmentation: a) sample image and segmentation of Fig. 7a: b) with 5 clusters and c) with 10 clusters. d) Another sample image and e) its segmentation with 15 clusters.

After segmentation, the classification continues evaluating each segmented cluster with the sample tissues using the index Q and a texture descriptor. This is illustrated in Figure 8 where the segmentation with k-Means was combined with the classification of Figure 7a using Sum Histogram.

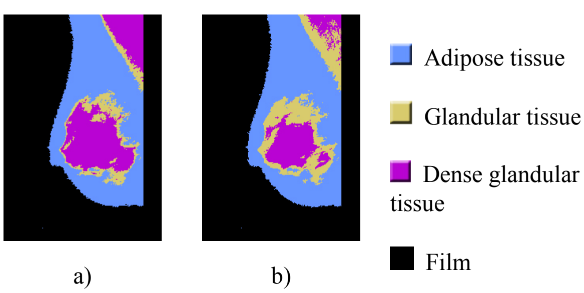


Figure 8. Combination of segmentation of k-Means and classification using the index Q applied with the Sum Histogram. a) k-Means with 10 clusters and b) *k*-Means with 25 clusters.

IV. Discussion

We presented the use of a fidelity index combined with texture descriptors to act in segmentation of breast tissues on mammograms. The exposed method brought the ability to characterize a breast tissue texture and identify it in different images. This characterization of breast tissue can help on the identification of healthy tissue, separating it from possible lesions.

It is important to observe that, as a mammography is a 2 dimensional projection of a 3 dimensional structure, it contains overlapping regions. Hence, the tissue classification presented does not identify a region with a pure tissue class, but a predominance of some tissue.

We also proposed a modification of the LBP descriptor that increased the performance of breast tissue identification. However, LBP still contains a major limitation as it was designed to work on squared regions.

In our last experiment with clustering algorithms, we presented the advantaged of a pixel-by-pixel approach for segmentation. The combination of texture descriptors with the index Q was used just as a classifying phase, with similar results of the classification through pre-segmented windows.

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