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A novel automatic breast density classification based in Nagao Filter and a priori dense segmentation

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Abstract— **Breast parenchymal density is considered a strong indicator of breast cancer risk. However, measures of breast density are qualitative and require the subjective judgment of radiologists. The American College of Radiology proposes a classification based on composition of the breast tissue. This standard is BI-RADS composition and is widely accepted for risk classification of mammograms. The objective of this work is to classify mammograms according to BI-RADS breast composition categories. We propose a novel automatic technique for classification based in homogenous filter applied to mammograms. The breast region is segmented from the surrounding and the breast region is divided in dense and fat regions. A Nagao filter is applied on the image. Mean and standard deviation are computed. These descriptors are used to classify the breast using support vector machines, decision tree and k-NN. We classified the pixels into the breast region with fuzzy C-Means with four clusters. For BI-RADS 1, the border for separated dense from fat tissue is given by the highest intensity cluster. For BI-RADS 2, BI-RADS 3 and BI-RADS 4, the border from the two highest clusters is used to separate dense from fat tissue. The results of a kappa test show good agreement (kappa mean =0.5584) with expert radiologists.**

I. Introduction

Breast cancer is leading the causes for cancer mortality among women. One in every eight women will develop breast cancer at some point in their lives [1]. In medicine where prevention and early diagnosis are very important, one of the most popular prevention exams is the study of breast parenchymal density through mammograms. The breast density is considered a strong indicator for breast cancer risk. For this reason, the American College of Radiologist (ACR) standardized numerical codes typically assigned by a radiologist after interpreting a mammogram. This standard is the Breast Imaging-Reporting and Data System (BI-RADS). However, this system standardizes patients in two domains: assessment categories (with a numerical code between 0 and 6, indicating pathology), and breast composition categories (with a numerical code between 1 and 4, indicating the density of breast tissue) [2]. The definition of the two BI-RADS domains is presented in Table I.

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TABLE I. BI-RADS DOMAINS.

Assessment		Composition	
Category	**Description**	**Category**	**Description**
0	Incomplete	1	Almost entirely fat
1	Negative	2	Scattered fibro-glandular densities
2	Benign findings	3	Heterogeneously dense
3	Probably benign	4	Extremely dense
4	Suspicious abnormality		
5	Highly suggestive of malignancy		
6	Known biopsy-proven malignancy		

The breast composition categories from BI-RADS are used for preventive tasks. However, the measures of breast density are qualitative and require the subjective judgments of radiologists. Therefore, the application of Computer Aided Diagnosis (CAD) software for the classification of images according to composition categories BI-RADS is necessary.

Different pattern classification approaches to differentiate breast tissue have been proposed. Most of them apply algorithms based on information theory [3], texture features [3], decision tree [4], k-Nearest Neighbor (k-NN) [4], filter bank [5], histogram information [6], Law's texture [7] and support vector machine [7].

We propose a novel approach based on the definition of BI-RADS composition categories analyzing the homogeneity of breast tissue structures (fat tissue for BI-RADS 1 and BI-RADS 2 and dense tissue for BI-RADS 3 and BI-RADS 4). The approach proposed is simple in comparison with others approaches [4], [6], [7].

In section II, we provide the steps of algorithm. This algorithm is composed of five parts: A) a pre-processing step, B) segmentation of breast, C) feature extraction from a filtered image, and D) a classification given by k-NN, a decision tree and Support Vector Machines (SVM). The algorithm not only classifies a given mammography, but it also provides a final segmentation. In section III, we show the results of the algorithm applied to a database of 1067 mammograms. Finally, we close the paper with a discussion in section IV.

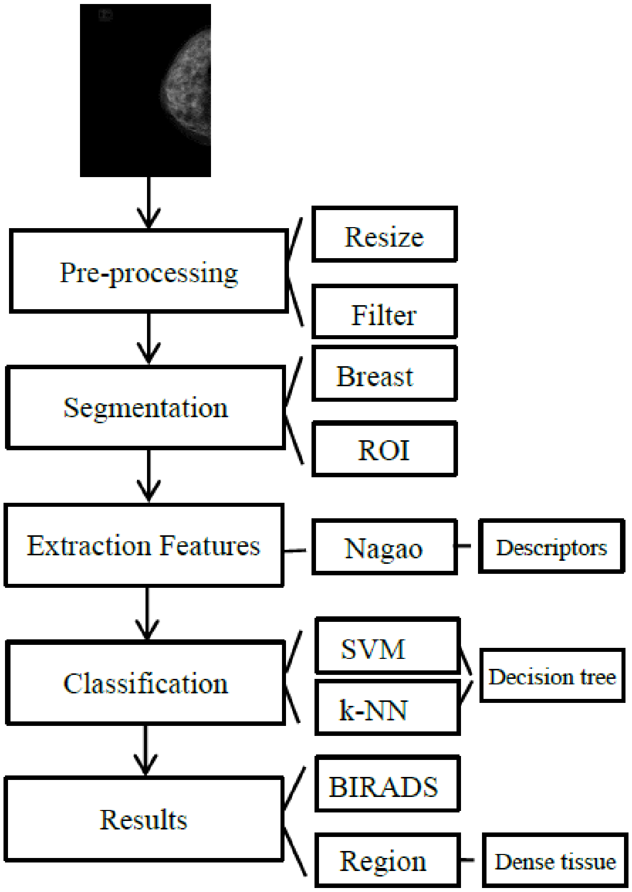

Figure 1. Flow diagram of the proposed classification algorithm.

II. Algorithm

Fig. 1 presents a block diagram of the different parts of the algorithm. The following lines will explain each phase.

A. Preprocessing Stage

Images are downsampled to $1/10^{th}$ of their original size providing a final resolution of 350 x 464 pixels for computational feasibility. Subsequently, a median filter of 3x3 is applied to eliminate effects from microtexture. Finally, a histogram expansion is applied to enhance the contrast of the image.

B. Breast Segmentation

The segmentation stage aims to separate the breast from the background and other objects that could be present in a mammographic image. We analyze the shape of the histogram of the background to select a threshold. If the histogram seems a Gaussian symmetric distribution, the threshold is given by two times the mode. Otherwise, we use the methodology presented in [8]. In this methodology, the rate of change of the standard deviation of a neighborhood is used to find the borders of interest.

After thresholding, the biggest area is identified as the breast. This area is used to limit a region of interest (ROI).

C. Extracted Features

In this step, we apply fuzzy C-Means (FCM) algorithm [9] with four clusters: high intensity pixels (dense tissue), semi-high intensity pixels (semi-dense tissue), semi-low intensity pixels (semi-fat tissue) and low intensity pixels (fat tissue). This approach provides a better differentiation among the different structures or types of tissues in the breast parenchymal. An initial or prior segmentation of the dense region is obtained by adding the two classes with highest and two with lowest intensity values.

Then, a homogeneous Nagao filter [10] is used. This filter calculates the variance of 9 sub-windows within a 5x5 moving window and replace the value of central pixel by the mean of the sub-window with the lowest variance (see Fig. 2). The result is a smoothed image with preserved edges.

The statistical descriptors (mean and standard deviation) are extracted for the three different regions (breast, dense and fat) from the images of textures after applying the Nagao filter.

D. Classification

The classification of mammograms according to composition categories BI-RADS was performed in three different ways: by SVMs, k-NN and decision tree classifiers.

SVMs are based on statistical learning [11], [12], [13], [14]. For our specific problem, a SVM for each class is used with a polynomial kernel. We build the training database from mammograms classified by expert radiologists and are selected by Fisher's linear discriminant [15].

In this work, we obtain a set of results from SVM and k-NN classifications. Both of them use the statistical descriptors described above. To classify BI-RADS 1 and BI-RADS 4 we use just SVM classifier. Finally, these results are taken as attributes in a decision tree classify.

E. Results and Dense Tissue

The decision tree produces as a result the classification of the mammography in one of the four breast composition categories from BI-RADS. Previously, it was assigned an a priori segmentation dense tissue segmented by fuzzy C-Means algorithm. Then, we determine the dense tissue according to the composition category BI-RADS: BI-RADS 1 (B1), BI-RADS 2 (B2), BI-RADS 3 (B3) and BI-RADS 4 (B4). If the mammography is classified as BI-RADS 1 the dense tissue is given by the highest cluster intensity pixel value, otherwise, the dense tissue is given by the a priori segmentation.

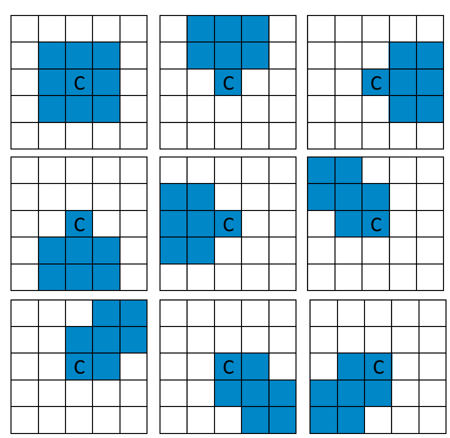

Figure 2. Sub-windows of Nagao filter algorithm.

III. EXPERIMENTAL RESULTS

A training set of 100 16-bit craniocaudal right mammograms was classified and manually segmented by eight radiologists with experience between 3 and 20 years. The database was uniformly distributed among the four BI-RADS classes. A kappa test [16], [17], [18], [19] and confusion matrices are used to evaluate the results. Table II shows the confusion matrices and kappa values. The kappa given by the training database is 0.635 ± 0.0588.

We validate the segmentation using the intersection of algorithm segmented area and a ground truth divided by the union of these. The ground truth was obtained by utilizing the STAPLE algorithm [20] on the radiologists' manual segmentation. To obtain the manual segmentation, we give predetermined segmentation (fuzzy C-Means with 2 clusters) and the radiologists using free hands tools modified the segmentation. The segmentation is showing in Fig. 3.We have an accuracy of 0.69±0.23 for BI-RADS 1, 0.72±0.18 for BI-RADS 2, 0.76±0.15 for BI-RADS 3 and 0.79±0.15 for BI-RADS 4.

Finally, we apply the algorithm to 1057 16-bits craniocaudal right mammograms. These mammograms were classified by eight radiologists. The kappa given by the set of mammograms was 0.56 ± 0.05. The result is showing at Table III.

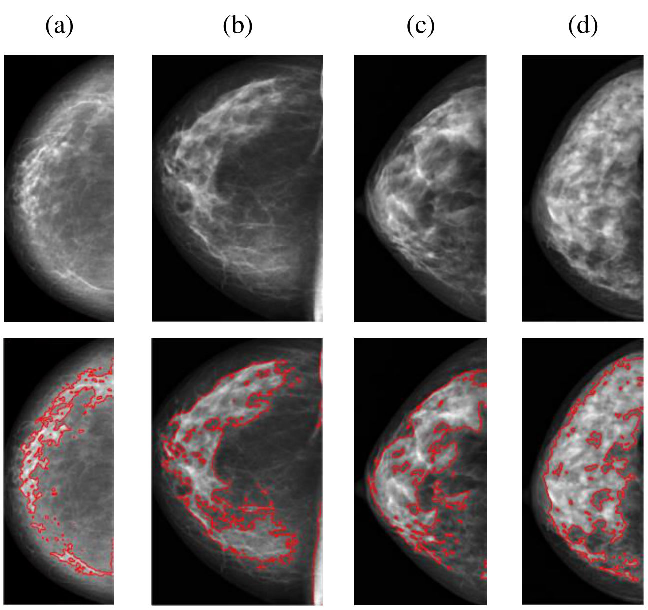

Figure 3. Algorithm segmentation according BI-RADS composition classification. *(Top: Mammograms, Bottom: Dense tissue segmentation, Left to right: Mammograms classified 1 to 4).*

TABLE II. CONFUSION MATRICES AND KAPPA VALUE FOR THE TWO MOST EXPERIENCED RADIOLOGISTS AND THE MODE OF EXPERTS APPLIED TO DATABASE

Expert 1 (k = 0.64)					
		Algorithm			
		BI	BII	BIII	BIV
Expert 1	BI	20	1	0	0
	BII	3	22	6	0
	BIII	0	10	3	15
	BIV	0	1	0	19

Expert 2 (k = 0.53)					
		Algorithm			
		BI	BII	BIII	BIV
Expert 2	BI	16	0	0	0
	BII	7	20	6	2
	BIII	0	13	3	18
	BIV	0	1	0	14

Mode (k =0.65)					
		Algorithm			
		BI	BII	BIII	BIV
Mode	BI	18	0	0	0
	BII	5	18	4	0
	BIII	0	14	4	10
	BIV	0	2	1	24

TABLE III. CONFUSION MATRICES AND KAPPA VALUE FOR THE MORE EXPERIMENT RADIOLOGISTS AND THE MODE OF EXPERTS APPLIED TO 1057 MAMMOGRAMS.

Expert 1 (k = 0.60)					
		Algorithm			
		BI	BII	BIII	BIV
Expert 1	BI	378	126	10	15
	BII	97	207	48	28
	BIII	9	39	21	50
	BIV	1	3	1	24

Expert 2 (k = 0.51)					
		Algorithm			
		BI	BII	BIII	BIV
Expert 2	BI	277	49	3	10
	BII	143	193	22	13
	BIII	35	132	52	74
	BIV	0	1	3	20

Mode (k = 0.57)					
		Algorithm			
		BI	BII	BIII	BIV
Mode	BI	284	49	2	10
	BII	182	246	34	14
	BIII	18	78	44	69
	BIV	1	2	0	24

IV. DISCUSSION AND CONCLUSIONS

In this paper, we propose a novel approach of computer-aided diagnosis to classify mammograms according to BI-RADS composition standard (Table I). Nagao filtering removes local textures in dense and fat regions. Simultaneously, it emphasizes the high intensities in dense regions and low intensities in fat regions. The filtered image improves the distance between categories in the feature space. Furthermore, according to the best of our knowledge, this filter has not been applied to mammograms yet.

This algorithm has been trained using the three first parts of algorithm and train SVM classifier. Then, it was tested with information from 8 expert radiologists. This is a larger number than previous work in this topic [4], [5], [21], [22]. Moreover, the algorithm has been tried in a large number of cases (over 1000). Therefore, another important contribution of this work is the database of mammographic images by itself.

The performance of the algorithm does not vary much from the training set of images to the testing set (see Table II and III). In [22], a better performance (kappa = 0.75) was reported. In that case, the authors just considered one expert radiologist to classify the 322 mammograms. Moreover, the training and test images were the same.

This work proposes a different method to analyze the dense tissue. For BI-RADS 1, the breast tissue is almost entirely fat, so the low intensity pixels are prevailing in the pixels distribution. Therefore, to assign the highest cluster given by fuzzy C-Means with 4 clusters allows better accuracy with dense tissue. For BI-RADS 2, BI-RADS 3 and BI-RADS 4, the pixels distribution allows to fuzzy C-Means to have a better classification of the different breast tissues.

Our novel approach has a good agreement with experienced radiologists, but it can be improved by adding other descriptors such as skewness.

This technique gives an alternative to qualitative evaluation and provides a tool for future studies in breast cancer risk with several data.

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