Breast Masses Classification using a Sparse Representation

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Abstract. Breast mass detection and classification in mammograms is considered a very difficult task in medical image analysis. In this paper, we present a novel approach for classification of masses in digital mammograms according with their severity (benign or malign). Unlike other approaches, we do not segment masses but instead, we attempt to describe entire regions of interest (RoIs) based on a sparse representation. A set of patches selected by a radiologist in a RoI are characterized by their projection onto learned dictionaries, constructed previously from classified regions. Finally, the region class was identified using a decision rule algorithm. The strategy was assessed in a set of 80 masses with different shapes extracted from the DDSM database. The classification was compared with a ground truth already provided in the data base, showing an average accuracy rate of 70%.

1 Introduction

Breast cancer is the most frequent disease in women and is considered as the largest public health problem in women population [1]. This disease is fully curable if diagnosis is achieved early and mammography is the more efficient method for visualizing abnormalities in the very early stages [17, 4]. However, mammographic interpretation is really hard and there exist studies showing that between 10% and 25% of breast cancer are not detected in mammography [3]. Abnormal lesions that are directly related to the presence of breast cancer are masses and calcifications. In clinical practices, a final diagnosis is determined by pathological analysis of abnormal lesions, an invasive procedure well known as biopsy. In order to reduce innecessary biopsies and interpretation variability between radiologists, the American College of Radiology diffused the *Breast and Imaging Report and Database System* (BI-RADS) as a classification standard to reporting breast lesions, which allows to classify different pathologies as well as their severity [2]. This standard established a basic classification for masses based on their shape, margin and density, which usually correspond to low level descriptors, and the severity level is defined a semantic interpretation of the first two features. In real clinical scenario, the radiologist identified the severity level of masses by visual features analysis, as circumbscribed margin of lesions, which are compact and lobular or circular shaped, and spiculated margin of lesions, which consist of a central mass with radiating spicules in some or many directions. Therefore , edge and shape information of mass defined a severity level (malign or benign lesion).

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Actually, Computer Aided Detection (CAD) and Diagnosis for mammography has decreased innecessary biopsy practice and variability effects since the radiologist can have a support for their diagnosis [16, 18, 15], becoming a well accepted clinical practice to assist radiologists interpreting mammograms, when they search and identify micro-calcification clusters [12]. However, the relatively low performance of CAD schemes in mass detection [7] make them less accepted as mass diagnosis tools. Two main factors makes breast mass detection in mammograms a very difficult task in medical image analysis. Firstly, there is a large variation in the appearance of both normal breast tissue and cancerous tissue [6]. Secondly, CAD systems are usually based on automatic detection and segmentation of abnormal lesions, issue that increases the false positive rate. As an alternative to overcome these difficulties, interactive CAD systems have been developed [18]. Given a query lesion, these systems identify other similar mass lessions in a large database, which are eventually clinically relevant to the actual one, allowing to provide a suggestion to the specialist in diagnosis tasks. On the other hand, CBIR-based CAD schemes [16] have the potential to provide radiologist with visual aid and increase their confidence in accepting CAD-cued results in the decision making process. In a recent work, we have proposed an interactive CAD system that provides a BI-RADS mass description of a manually selected region of interest (RoI) by region-based descriptors [13].

In this paper, a new approach for breast mass classification from a set of regions of interest (RoIs) is proposed. A set of image patches are extracted from previously classified RoIs and then characterized using a multi-scale edge analysis to project them in a feature space, using a sparse representation. This process allows to identify feature clusters that corresponds to the severity of the masses (malign or benign). Finally, a new RoI can be classified by projecting some patches in the feature space and analyzing their relationships with the severity clusters. This strategy was assessed in a set of 80 masses with different shapes extracted from the DDSM database, where 30 benign and 30 malign masses were used as the training set and the remaining 20 masses were selected for testing. The classification was compared with a ground truth already available in the data base, showing an accuracy rate of 70%.

2 Methodology

The proposed method for classification of breast masses can be roughly divided in two stages: an offline learning process and an online classification procedure. At the offline learning process, the main goal is to identify the feature vectors that characterize each selected class, in this case, malign and benign masses. For doing so, three different tasks are involved in this process. First, two different sets of RoIs with benign and malign masses are selected by a radiologist and preprocessed to enhance the mass shape characteristics. As the class characterization process will be based in a sparse representation, the next step in the learning process includes to construct malign and benign severity dictionaries. Then, an image patch dictionary is constructed for each selected class by randomly sampling patches from malign and benign RoIs, which are thus characterized with a multi-scale edge analysis. Finally, a new set of relevant patches (that capture edge and background information) are manually selected at each RoI (Figure

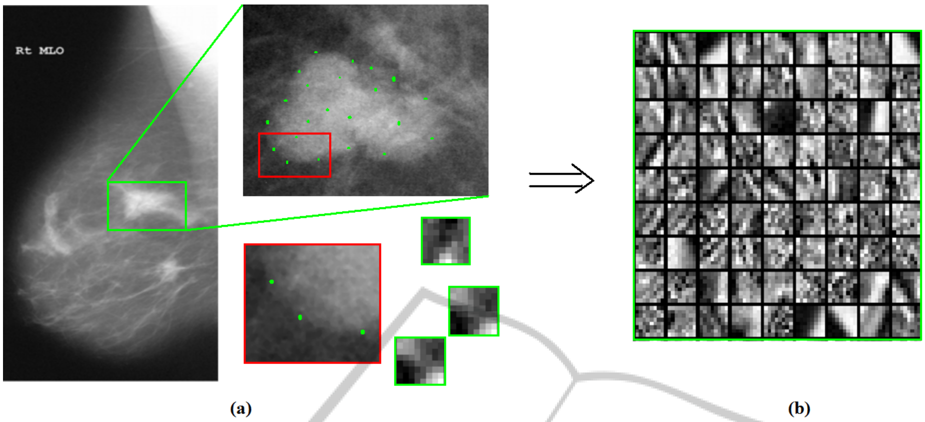

Fig. 1. Point selections by radiologist and sparse representation. (a) illustrates a manual selection of the patches as points of interest. (b) illustrates the dictionary formed by the selection of patches.

1(a)) and then characterized with a sparse representation, by using its projection onto the malign and benign severity dictionaries previously constructed (Figure 1(b)).

The online classification procedure takes place when the severity of a test RoI needs to be defined. The radiologist manually select a set of patches on the test RoI, which are individually classified using again a sparse representation. Each patch is then projected onto the malign and benign severity dictionaries, and these projections are then compared with the characterizations previously obtained for the training patches. This process, followed by a decision rule, allows to establish the membership of the entire RoI.

2.1 RoI Pre-processing

Mammography analysis generally must deal with regions difficult to interpret [6], since they are associated to hard acquisition conditions. In most cases, diagnostic characteristics, such as mass edges, are small and have low contrast with respect to the surrounding breast tissues. To improve the particular region characteristics and to highlight the grey level intensity information, a preprocessing stage was carried out on each RoI. A contrast enhancement method is then used based on mean and standard deviation information of each RoI, allowing to stretch the maximum and minimum gray levels to the interval $[0, 255]$. With this procedure shape features are improved, while preserving edge details. Finally, the whole region is smoothed using a median filter [19].

2.2 Dictionary Construction

The next step is to build dictionaries $\mathbf{D}_m$ and $\mathbf{D}_b$ for malign and benign masses, respectively, as arrays of patches (atoms). Such an approach has been successfully used for image classification [9]. We selected a set of N RoIs with different mass shapes, according to their level of severity (malign or benign) as training RoIs. First, a set of K random patches per RoI were selected and then characterized using a multi-scale edge analysis. This analysis attempts to describe the tissues present in mammographic images in terms of edge and background information. We used the 3×3 and 5×5 Sobel kernels, applied in the horizontal and vertical directions, and concatenated as a single feature vector. Finally, this vectors are stored as columns of the matrices $\mathbf{D}_m$ and $\mathbf{D}_b$, leading to 2 different dictionaries that represent the mass severity, one for malign and one for benign masses. This process is illustrated for the benign dictionary in Figure 2.

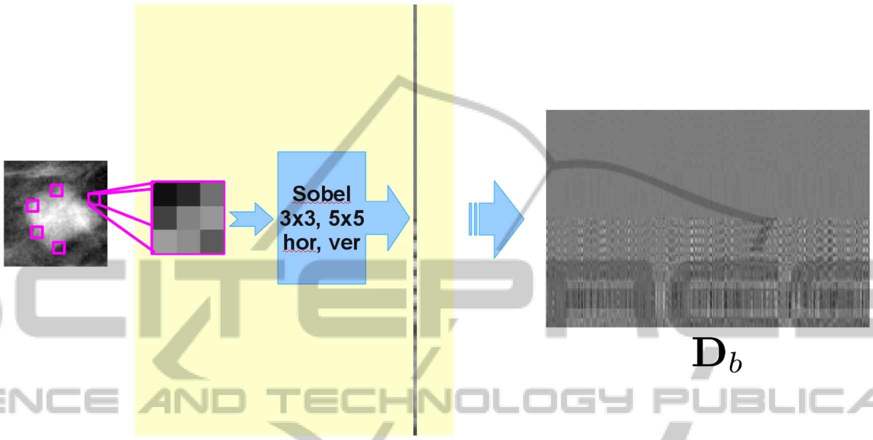

Fig. 2. Construction of a feature dictionary for benign masses.

2.3 Sparse Representation and Characterization

Once the dictionaries are built, the main goal is to identify the set of feature vectors that characterizes the benign and malign classes. Therefore, a new set of patches selected from the training images are projected onto the previously constructed dictionaries, following a sparse representation. The coefficients of the projection will be used to place each patch on a feature space, where each class will be defined as clouds of feature points.

Sparse representation techniques allows to identify the constituent parts of a scene and then, using some of them, the same scene or similar ones may be accurately reconstructed. These parts, denoted as basis functions or patches (atoms), are usually arranged in overcomplete dictionaries with a larger number of elements than the effective dimensionality of the input space, thereby representing a wider range of image phenomena [14, 11]. Formally, consider a $n \times m$ matrix $\mathbf{D}$, where each column is a possible image in $\mathbb{R}^n$ (atomic images), a dictionary of patches. The projection of an image x onto the space spanned by $\mathbf{D}$ yields a weighting vector α ($x = \mathbf{D}\alpha$). Furthermore, if α is sparse (with $k_0 \ll m$ nonzeros), this produces a linear combination of k_0 patches with varying weights. To find the adequate α, we need to solve the optimization problem denoted as $\mathcal{G}_1(\mathbf{D}, x, \lambda)$, which has the form

$$\mathcal{G}_1(\mathbf{D}, x, \lambda) : \min_{\alpha} \lambda \|\alpha\|_1^1 + \frac{1}{2}\|x - \mathbf{D}\alpha\|_2^2$$

The solution of this problem consist in finding the sparsest vector α that weights x as a linear combination of patches from $\mathbf{D}$, using the norm ℓ_1 as a measure of sparsity. Different approximation methods to solve this problem have been recently proposed, detailed descriptions and references can be found in [5]

This process, applied independently to the benign and malign RoI sets, delivers a set of representation coefficients per class (a set of α vectors obtained by solving the optimization problem), which allows to characterize the entire class as a set of feature points. After a new set of k relevant patches are manually selected for capture additional mass information from the training RoIs, these are characterized using a multi-scale edge analysis and projected onto the previously constructed dictionaries, following a sparse representation, in terms of $x = \mathbf{D}\alpha$, where x is the feature vector of a RoI patch and α corresponds to the projection coefficients of x. $\mathbf{D}$ is replaced by $\mathbf{D_m}$ if the patch belongs to a malign RoI or by $\mathbf{D_b}$ if the patch comes from a benign RoI. This coefficients allow to represent each patch in a feature space, thus defining each class (malign or benign) as clouds of feature points in this space.

2.4 Classification

When a new RoI under analysis arrives, a mass classification strategy that uses the K-NN rule (K-Nearest Neighbor) was implemented. First, a set of patches are manually selected at the test RoI, and then characterized by proyecting each patch onto the severity dictionaries $\mathbf{D}_m$ and $\mathbf{D}_b$. For each patch, two different representation coefficients are obtained after applying the sparse representation framework (described in Subsection 2.3), one indicating the projection onto the benign dictionary, α_b, and the other one describing the projection onto the malign dictionary, α_m. Then, the complete set of coefficients is located as a set of points in the feature space, and each point is classified as benign or malign using the k-nearest neighbors algorithm. The algorithm used a weighted Mahalanobis distance (wd) to measure the similarity among the points in the feature space describing both the benign and malign class.

Finally, the classification of the entire RoI, S^I, is obtained by applying a decision rule [13], which uses each classified point, weighted by the distance to the nearest neighbor, to infer the corresponding class for the RoI. The decision rule can be written as follows

$$S^I = \arg\max_{S_i} |S_1, S_2|, \quad S_i = \sum_{i=1}^{K} w_d^{s_i}, \quad i = 1, 2 \tag{1}$$

where S_1 and S_2 corresponds to benign and malign classes, respectively, and $w_d = 1/d(\boldsymbol{x}, \boldsymbol{y})$ is the point weight, calculated as the Mahalanobis distance between the nearest neighbor ($\boldsymbol{y}$) and the actual point ($\boldsymbol{x}$).

3 Preliminar Results

A small set of 80 regions, extracted from the *Digital Database for Screening Mammography (DDSM)* [8], were used to preliminary evaluate the performance of the proposed approach. Each RoI was previously classified as benign or malign by a group of breast radiologists, according the BI-RADS standard. The set of RoIs was splitted into two training sets (30 benign RoIs and 30 malign RoIs) and one testing set (20 RoIs). The training set was used for constructing the $\mathbf{D}_m$ and $\mathbf{D}_b$ dictionaries, 60 image patches (size: 3×3 pixels) were randomly sampled from each training RoI, leading to two severity dictionaries, each one containing 1800 patches. Then, to characterize each class in the feature space, 900 feature points were used per class, obtained after applying the sparse representation framework to 30 manually sampled patches per each training RoI. For the sparse representation, we have used the SparseLab[1] library that provides a set of solvers for the optimization problem (from this library we have chosen the Basis Pursuit solver).For classification of each test image, 30 manually sampled patches were Selected per RoI, and then projected onto the two severity dictionaries, leading to a set of 60 feature points. The optimal number of k for the k-nearest neighbors algorithm was estimated by a 10-fold cross validation assessment. Results showed that a minimal of 11 neighboring feature points are needed for establish optimally the corresponding severity level.

Classification performance was assessed by computing the accuracy rate from a confusion matrix of the test images, according to the ground truth provided with the DDSM mammogram database (defined by experienced radiologists). The accuracy was defined as:

$$\text{Acc} = \frac{(TP+TN)}{(TP+TN+FP+FN)}$$

where TP, TN, FP and FN stand for true positives, true negatives, false positives and false negatives, respectively. From the 20 test regions, 5 benign RoIs and 9 malign RoIs were correctly classified, leading to an accuracy rate of 70%. This results are reported in the Table 1.

Table 1. Confusion Matrix for classification of 20 test RoIs.

	Benign	Malign
Benign	5	4
Malign	2	9

4 Conclusions

In this paper a new strategy for breast mass classification from mammography images based on a sparse representation scheme was proposed, implemented and evaluated. This strategy provided a BI-RADS mass classification of a RoI as benign or malign, which was supported by a set of diagnosed images that were previously classified by expert radiologists. Instead of attempting to segment masses, we proposed a mass feature description, based on its internal structure with no explicit mass boundary detection.

The proposed approach was evaluated on a public image database (DDSM). The preliminar results have shown that this approach is successfully able to classify the severity of a RoI using learned dictionaries. Even though the proposed classification

[1] http://sparselab.stanford.edu/

scheme have been tested with a small dataset, the obtained accuracy of 70% seems to be promising for automatic classification of breast masses. These preliminary results have opened up new strategies for the development of computer-aided tools, based on the sparse representation framework, for mammographic diagnosis. Further work includes to perform extensive validations with bigger datasets and to include other breast mass characteristics, like shape, margin and density.

References

1. American Cancer Society: American Cancer Statistics. (2007) Updated: September 2, 2008.
2. American College of Radiology (ACR): Illustrated Breast Imaging Reporting and Data System (BI-RADS). ACR (1998)
3. R. Bird, T. Wallace, and B. Yankaskas, Analysis of cancers missed at screening mammography, Radiology 178 (1992), 234–247.
4. S. Buseman, J. Mouchawar, N. Calonge, and T. Byers., Mammography screening matters for young women with breast carcinoma., Cancer 97 (2003), 352–358.
5. A. M. Bruckstein, D. L. Donoho, and M. Elad., From Sparse Solutions of Systems of Equations to Sparse Modeling of Signals and Images., SIAM Review 51 (2009), 34–81.
6. H. D. Cheng, X. J. Shi, R. Min, L. M. Hu, X. P. Cai, H. N. Du. Approaches for automated detection and classification of masses in mammograms., Pattern Recognition 39 (2006), 646–668
7. D. Gur, J. S Stalder, L. A. Hardesty, B. Zheng, J. H. Sumkin, D. M Chough, B. E. Shindel, and H. E. Rockette, Computer-aided detection performance in mammographic examination of masses: assessment., Radiology 233 (2004), 418–423.
8. M. Heath, K. Bowyer, D. Kopans, R. Moore, and W. P. Kegelmeyer, The digital database for screening mammography, in Proceedings of the Fifth International Workshop on Digital Mammography, Medical Physics Publishing M.J. Yaffe, ed (2001), 212–218.
9. J. Herredsvela, K. Engan, T. O. Gulsrud, and K. Skretting, Detection of masses in mammograms by watershed segmentation and sparse representation using learned dictionaries. (paper in pdf-format), Proceedings NORSIG (2005), 35–40.
10. H. Kim and J. Kim, Region-based shape descriptor invariant to rotation, scale and translation., Signal Proc.: Image Communication 16 (2000), 87–93.
11. S. G. Mallat and Z. Zhang, Matching pursuits with time-frequency dictionaries, IEEE Transactions on signal processing 41 (1993), no. 12, 3397–3415.
12. R. M. Nishikawa, Current status and future directions of computer-aided diagnosis in mammography, Computerized Medical Imaging and Graphics 31 (2007), 224–235.
13. F. Narvaez, G. Diaz, E. Romero, Automatic BI-RADS description for mammographic masses, IWDM2010 Digital Mammographhy, LNCS 6136 (2010), 673–681.
14. B. A. Olshausen, Principles of image representation in visual cortex, pp. 1603–1615, MIT Press, 2003.
15. N. A. Rosa, J. C. Felipe, A. J. Traina, R. M Rangayyan, and P. M. Azevedo-Marques, Using relevance feedback to reduce the semantic gap in content-based image retrieval of mammographic masses., Conf Proc IEEE Med Biol Soc (2008), 406–409.
16. Y. Tao, S. B. Lo, M. T. Freedman, and J. Xuan, A preliminary study of content-based mammographic masses retrieval, Proc SPIE 6514 (2007), 65141Z.
17. K. Verma and J. Zakos, A computer-aided diagnosis system for digital mammograms based on fuzzy-neural and feature extraction techniques, IEEE Transactions on Information Technology in Biomedicine 16 (2002), 219–223.

18. B. Zheng, C. Mello-Thoms, X. H. Wang, G. S. Abrams, J. H. Sumkin, D. M. Chough, M. A. Ganott, A. Lu, and D. Gur, Interactive computer aided diagnosis of breast masses: Computerized selection of visually similar image sets from a reference library, Academical Radiology 14 (2007), 917–927.
19. K. Wongsritong, K. Kittayaruasiriwat, F. Cheevasuvit, K. Dejhan, A. Somboonkaew. Contrast enhancement using multipeak histogram equalization with brightness preserving., IEEE Asia-Pacific Conference on Circuits and Systems Proceedings, (1998), 455–458