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Combination of Different Texture Features for Mammographic Breast Density Classification

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***Abstract*—Mammographic breast density refers to the prevalence of fibroglandular tissue as it appears on a mammogram. Breast density is not only an important risk for developing breast cancer but can also mask abnormalities. Breast density information can be used for planning individualized screening and treatment. In this work, statistical distributions of different texture descriptors and their combination are investigated with Support Vector Machines (SVMs) for objective breast density classification: Scale Invariant Feature Transforms (SIFT), Local Binary Patterns (LBP) and texton histograms. SIFT is an approach for detecting and extracting local feature descriptors that are reasonably invariant to changes in illumination, image noise, rotation, scaling and small changes in viewpoint. The SIFT descriptor is a coarse descriptor of the edges found in the keypoints. LBPs provide a robust and computationally simple way for describing pure local binary patterns in a texture. They provide information regarding the prevalence of different edge patterns and uniformity. Textons are defined under the operational definition of clustered filter responses and provide a statistical and structural unifying approach for texture characterization. The breast density classification accuracy of the SVM classifiers modeled on the histograms of the three different sets of texture features separately and their combination is evaluated on the Medical Image Analysis Society (MIAS) mammographic database and the results are presented. The combination of the statistical distributions of all the different texture features allows for the highest classification accuracy, reaching over 93%.**

***Index Terms*—breast density, texture, Local Binary Patterns, Scale Invariant Feature Transforms, textons.**

I. INTRODUCTION

Mammographic breast density refers to the prevalence of fibroglandular tissue as it appears on a mammogram. It has been shown to be one of the most important risks for developing breast cancer [1], [2], [3], [4]; first reported by Wolfe in 1976 [5]. Breast density is associated with both lower sensitivity and an increased rate of interval cancers. It is an inherent trait, but can be altered by endogenous and exogenous hormonal factors, elective estrogen receptor modulators, diet and generally declines with age [4]. Better understanding of breast density and how it corresponds to a significant increase of breast cancer risk as well as the case that cancers in dense breasts are more often mammographically occult [6] have led to the need of breast density assessment and use of the information for supplementary screening using other imaging techniques such as whole-breast ultrasound (US) [7]. Information regarding breast density has also been shown to be cost-effective strategy for sharing risk information that may become useful in prevention decisions as women given such information reported being very likely to have an annual clinical breast examination in addition to their screening mammogram [8].

X-ray mammography has been the method of choice for breast cancer population screening. With the development of novel breast imaging techniques and the endeavor to move towards individualized screening and prevention, mammographic breast density can be used to establish appropriate plans. In the case of dense breasts use of whole breast ultrasound has been shown to significantly increase breast cancer detection despite a corresponding increase in false positives [9]. Magnetic Resonance Imaging (MRI) can also be used for screening in dense breasts. In addition to US tomosynthesis may be useful in addition to mammography for reduction false positive recalls especially in dense breasts [10].

Thus, breast density and change thereof may be used for risk assessment, for reducing screening intervals, for the development of Computer Aided Detection (CAD) systems with higher sensitivity and specificity, but most importantly for signaling the necessity for developing individualized risk evaluation, screening and treatment for achieving the earliest possible diagnosis for the best prognosis. Mammographic breast density is a powerful breast cancer risk factor that has considerable potential in risk stratification and in monitoring the effects of interventions in risk alteration. Yet, the need still exists to develop objective methods that provide precise, simple and reproducible density measures to achieve this [4].

Following Wolfe's mammographic breast parenchymal density categorization [5], the American College of Radiology proposed the Breast Imaging Reporting and Data System (BI-RADS) [11] mammographic parenchymal density classification as follows:

- (i) the breast is almost entirely fat,
- (ii) there are scattered fibroglandular densities,
- (iii) the breast is heterogeneously dense which may lower the sensitivity of mammography, and
- (iv) the breast tissue is extremely dense, which could obscure a lesion in mammography.

a. b. c. d.

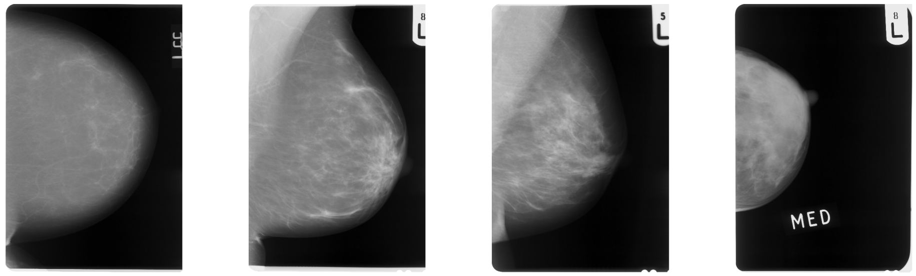

Fig. 1. Examples of mammograms from the breast parenchymal density BI-RADS classes a) BI-RADS I, b) BI-RADS II, c) BI-RADS III, d) BI-RADS IV.

The first two classes correspond to low density, low risk mammograms whilst BI-RADS mammographic breast density classes *III* and *IV* correspond to high density, higher breast cancer risk classes. The four BI-RADS mammographic breast density classes can be seen in Figure 1.

Different computer aided techniques and methodologies have been developed for more objective and reproducible mammographic breast parenchymal density evaluation and classification, which fall in two main categories: qualitative and quantitative [4]. These include physics based models and evaluation of different parameters based on intensity and/or texture. Byng et al. [12] propose a semi-automatic area based quantitative computer measure. Interactive thresholding and the percentage of the segmented dense tissue over the segmented breast area provide a relative quantitative evaluation of breast parenchymal density. The method which is implemented in Cumulus^{TM} software is most widely used for density classification. The Standard Mammogram Form (SMF) provides the height of interesting tissue i.e. volume of non-fat tissue in the breast [13] and more recently Volpara^{TM} which uses a relative - rather than an absolute - physics model which reduces the need for accurate imaging physics data [14].

As breast density is evaluated on the 2D projection of the breast on the mammogram, a number of breast density classification methods have used different texture based features for density classification. Miller and Astley [15] investigated texture-based discrimination between fatty and dense breast types applying granulometric techniques and Laws texture masks. Petroudi et al. [16] proposed a scheme that uses statistical based texton models to capture the mammographic appearance within the breast area. Musta [17] et al. presented an overview of the accuracy of different breast density classification methods using different features, and achieve a maximum classification accuracy of 73.3% through a selection of Haralick and Soh texture features, genetic search and wrappers. Kallenberg et al. [18] developed a breast density segmentation algorithm using a set of different features with information about location, intensity, texture and global context with a neural network for pixel classification intensity. Keller et al. [19] used adaptive Fuzzy Mean Clustering combined with Support Vector Machines (SVMs) for cluster tissue classification. He et al. [20] calculated different texture features on the grey-level intensity histograms to characterize different mammogram blocks to different tissue types and used a binary model based Bayes classifier for BI-RADS mammogram classification.

This paper investigates the use of histograms of different texture features: Scale Invariant Feature Transforms (SIFT) [21], Local Binary Patterns (LBP) [22], texton histograms [23] and their combination evaluated on mammograms with SVMs [24] for breast parenchymal density classification. The method is developed and quantitatively evaluated using the Medical Image Analysis Society (MIAS) mammogram database [25] and the provided 3 category density classification.

II. METHOD

For breast density characterization the mammograms are pre-processed and normalized as in [16] and the mammographic breast region is segmented. Following, the different features are evaluated on the segmented breast region. Each training image is represented by a vector(s)/histogram(s), and SVMs [24] are trained to discriminate vectors corresponding to positive and negative training images. Finally the trained SVMs are applied to testing images.

A. Evaluation of the texture features

Three different texture features are evaluated and combined for density characterization: SIFT, LBP and textons. SIFT is an approach for detecting and extracting local feature descriptors that are invariant to translation, scaling, and rotation, and partially invariant to illumination changes and affine or 3D projection [21]. LBPs provide a robust and computationally simple way for describing pure local binary patterns in a texture with low computational complexity and relatively insensitive to changes in illumination [22]. Textons are defined under the operational definition of clustered filter responses [26] and provide a statistical and structural unifying approach for texture characterization [23].

1) Scale Invariant Feature Transform - SIFT: The SIFT approach which was proposed by Lowe [21] transforms an image into a collection of local feature vectors which are translation, scaling and rotation invariant and has been shown to be a robust keypoint descriptor in different image classification, retrieval and matching applications [27]. SIFT provides keypoint detection through the identification of interesting points in the scale space. The SIFT descriptor is a coarse descriptor of the edges found in the keypoints. First the images are convolved with Gaussians at different scales and the Differences of Gaussians images are generated from the adjacent smoothed images. The detection stages for SIFT features include scale space extrema detection where the interesting points are identified as local extrema of differences of Gaussians, keypoint localization through interpolation of nearby data, orientation assignment where the gradient orientation histogram is computed in the neighborhood of the keypoint and generation of keypoint descriptors. Once a keypoint orientation has been selected, the feature descriptor is computed as a set of orientation histograms (with 8 bins) on 4 x 4 pixel neighborhoods. The SIFT features were first used for breast density classification by Bosch et al. [28].

The SIFT descriptors are computed on a regular grid with spacing *M* pixels over N regular support patches, as in [28]. A SIFT keypoint vocabulary is build through vector quantization of descriptors from a set of training images using k-means (k$\sim$ 1000). Following each descriptor is assigned to the one closest to it in the SIFT vocabulary and the images are represented with corresponding histograms.

2) Local Binary Patterns - LBP: LBPs are evaluated by calculating the local binary difference between the gray value of a pixel x (i.e. central pixel) and the gray values of P pixels in a local neighborhood of x placed on a circle of radius R [22]. An LBP code for a neighborhood is produced by multiplying the thresholded values with weights given to the corresponding pixels, and summing up the result. However, this representation is rotationally variant, thus Ojala et al. [22] introduced rotational invariance by performing P - 1 bitwise shift operations on the binary pattern and selecting the smallest value. The number of changes between the zeros and ones in the pattern signify whether the corresponding local texture is uniform i.e. there are a limited number of transitions or discontinuities in the circular presentation of the pattern. [29]. A pattern is defined uniform if the number of transactions between 0 and 1 of the sequence is less or equal to two. The most frequent uniform binary patterns correspond to edges, corners, and spots and can be regarded as important feature detectors triggered by the best matching pattern.

Here, the basic LBP code for a neighborhood is used, produced by multiplying the thresholded values in the central pixel's local neighborhood with weights given to the corresponding pixels, and summing up the result [22]. For each pixel x, an 8-bit number $b_1\, b_2\, b_3\, b_4\, b_5\, b_6\, b_7\, b_8$ is created, where $b_i = 0$ if neighbor i has value less than or equal to the central pixel's x value and 1 otherwise. The histogram of all the corresponding values for the all the pixels is evaluated to describe the given image.

3) Statistical Distribution of Textons: Textons, as proposed by Julesz [30], are the primitives of texture, and structural models of texture are based on the view that texture are composed of primitives in spatial arrangements. For the purposes of this work textons are defined under the operational definition of Leung and Malik [26] as clustered filter responses. Evaluation of the texton histogram for a mammogram follows the methodology presented in [16].

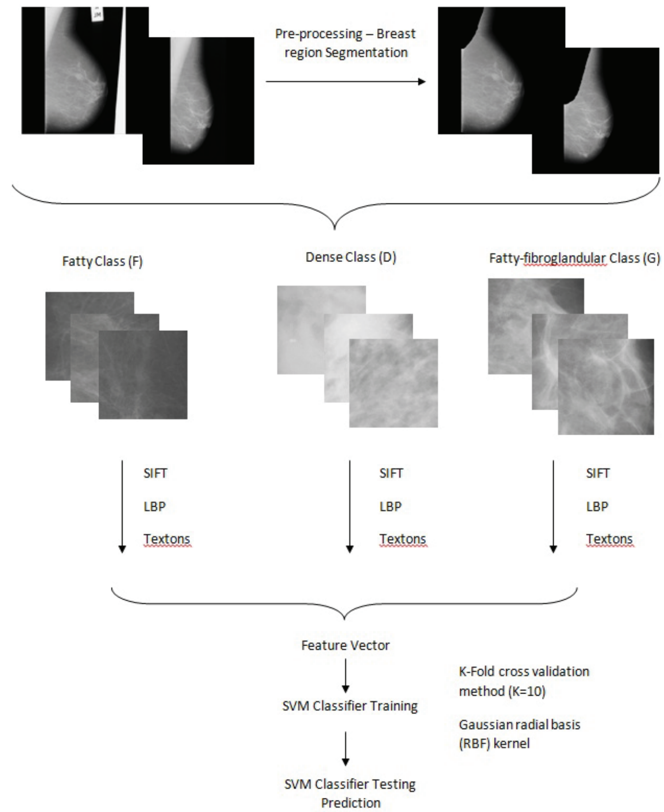

Fig. 2. Breast density classification presented methodology.

For the evaluation of the texton statistical distribution the following steps need to take place. Initially the texton dictionary must be derived. Following, segmentation of the breast region [31] the resulting images from the training set are filtered using the Maximum Response 8 (MR8) filter bank proposed by Varma and Zisserman [23]. After the filtering using the filter bank, each pixel is associated with a vector that holds the filter response corresponding to each filter in the filter bank. The filter responses over all the pixels in the images' regions of interest are aggregated. The texton dictionary is created by clustering these aggregated filter responses over all images with 10 textons per breast density class using the K-Means algorithm.

Given the texton dictionary, each image pixel in the breast region of each mammogram is mapped to the texton closest to it in the filter response space. This step provides the image's texton map on which the texton histogram, showing the relative frequency of occurrences of the textons in the texton dictionary is evaluated.

B. Support Vector Machines

Mammographic breast density classification of the different texture histograms is achieved using SVMs. SVMs [32], [24] are chosen because of their ability to generalize well in high dimensional spaces. They are based on statistical theory and aim to determine the location decision boundaries that result in the optimal separation of classes [24]. SVMs nonlinearly map the training data in the input space using a kernel function to a higher dimensional feature space. Kernel functions are applied to describe a similarity relationship between the sets to be classified. Following, SVMs determine a decision boundary in the feature space to distinguish the classes by creating the optimal separating hyperplane [24]. In the two-class problem, where the classes are linearly separable the SVM selects the linear decision boundary that minimizes the generalization error. The method finds the hyperplane that leaves the largest possible fraction of points of the same class on the same side, while maximizing the distance of either class from it. This optimum hyperplane is produced by maximizing the minimum margin (i.e. the sum of the distances to the hyperplane from the closest points of the two classes between the two sets). Thus, the resulting hyperplane is depended on border training patterns only called support vectors.

SVMs have been shown to generalize well on difficult image classification problems where the only features are high dimensional histograms [33]. SVMs are therefore investigated using the statistical distributions of the different texture features as presented above and their combination, representing different characteristics of the breast regions. The methodology for the combination of the different texture statistical distribution vectors and SVM classification is shown in Fig. 2. Different kernel functions were also investigated and the Gaussian Radial Basis Function (RBF) was chosen as it resulted in the best separation between the different density classes. Since the SVMs were originally developed for two-class classification, for the multi-class breast density classification an ensemble of binary classifiers is used, where a binary classifier is trained for each pair of classes. The decision is then taken by combining the partial decisions of the single members of the ensemble [34]: unknown images are classified using majority voting strategy among them. Tenfold cross validation is used for training and evaluating the corresponding SVMs.

III. Results

The algorithm is evaluated on a set of mammograms from the MIAS mammographic database [25]. The MIAS database contains 322 mammograms corresponding to 161 cases. The mammograms in the database are classified to three different density classes, fatty, fatty-glandular and dense glandular. Thus for the purposes of this work the mammograms are automatically classified to one of these three classes. Since there is different representation of the three classes in the database, only 62 mammograms are chosen per density class.

The performance of the SVMs evaluated for breast density classification using tenfold cross validation modeled on each of the histograms of the corresponding texture features is shown in Table I. The best agreement with the density annotations provided with the MIAS database was 93.5484%. Accuracy is calculated as the percentage of correctly classified mammograms in a breast parenchymal density category over the ground truth total number of mammograms in that category. Figure 3 shows the classification for each of the mammograms in every category.

TABLE I
CLASSIFICATION ACCURACY RESULTS FOR THE MIAS BREAST DENSITY CHARACTERIZATION USING SVMS MODELED ON THE REPORTED TEXTURE FEATURES STATISTICAL DISTRIBUTIONS

MIAS Density Classification SVM trained on	**Accuracy%**
SIFT	74.7312%
LBP	82.7957%
Textons	75.8065%
SIFT-LBP-Textons	93.5484%

IV. Discussion

This paper investigates the use of SVMs with different statistical distributions of different texture features i.e. SIFT, LBP and textons. The classification accuracy for the SVM when all texture feature distributions are used reaches over 93%. The different texture features used seem to capture different breast region characteristics. The SIFT captures local oriented features over different visual scales. LBP provide information whether the region of interest (ROI) is relatively uniform. Textons can be through of as the building blocks of the present texture the same way phonemes make up speech [30].

The presented method compares favorably with other methods presented in the literature. Petroudi et al. [16] evaluated texton histograms using chi-square distance achieved a classification accuracy of 76% but on a different database. Blot and Zwiggelaar [35] using Gray Level Co-occurrence matrices and a method by Karssemeijer [36] achieve 65% accuracy for classifying the MIAS images to the MIAS given 3-class density categorization [25]. Bosch et al. [28] used a combination of SIFT and textons histograms resulting form local image patches achieving a classification accuracy of 91.4%. Oliver et al. [37] extracted morphological and texture features from the segmented breast areas and used a Bayesian combination of a number of classifiers achieving 84% accuracy.

From the evaluation of the SVMs with the histograms of the different texture feature one can see that the LBPs achieve the best classification accuracy when used alone, whilst training the SVM with the SIFT features' histogram achieves the worst classification result. Further investigation of the different parameters for the evaluation of the different SIFT features is warranted. In addition, the SVMs achieve the highest classification when they are trained on all the different texture features distributions. However, these distributions have different sizes. Different combinations of different features with different classifiers may result in better classification accuracy.

V. Conclusion

Different texture features and their combination are used with SVMs for breast density classification. Training the

a. b. c. d.

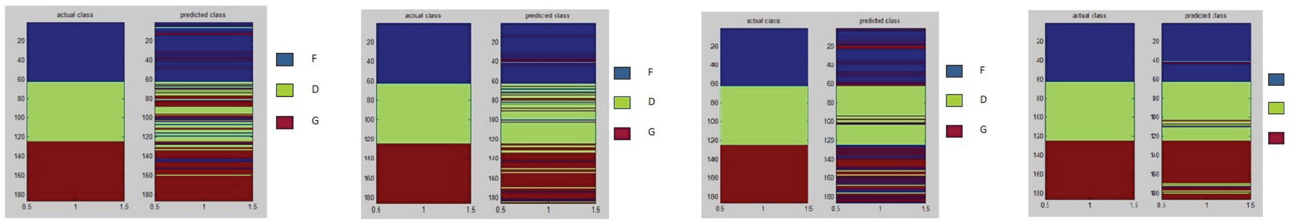

Fig. 3. The breast density classification results for the mammograms from the MIAS database. The results are shown separately for the SVMs trained with the statistical distributions of the different texture features: a) SIFT, b) LBP, c) Texton, d) SIFT-LBP-Texton.

SVM on the statistical distributions of all the texture features results in the best classification accuracy of 93.4%, when evaluated on the MIAS [25] database on the the corresponding 3-category classification provided. Future work will involve the use of different classifiers and classification methods for density classification. In addition, the corresponding features will be evaluated for the segmentation parenchymal densities in mammograms.

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