False Positive Reduction in Breast Mass Detection using the Fusion of Texture and Gradient Orientation Features

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Abstract. The presence of masses in mammograms is among the main indicators of breast cancer and their diagnosis is a challenging task. The one problem of Computer aided diagnosis (CAD) systems developed to assist radiologists in detecting masses is high false positive rate i.e. normal breast tissues are detected as masses. This problem can be reduced if localised texture and gradient orientation patterns in suspicious Regions Of Interest (ROIs) are captured in a robust way. Discriminative Robust Local Binary Pattern (DRLBP) and Discriminative Robust Local Ternary Pattern (DRLTP) are among the state-of-the-art best texture descriptors whereas Histogram of Oriented Gradient (HOG) is one of the best descriptor for gradient orientation patterns. To capture the discriminative micro-patterns existing in ROIs, we propose localised DRLBP-HOG and DRLTP-HOG descriptors by fusing DRLBP, DRLTP and HOG for the description of ROIs; the localisation is archived by dividing each ROI into a number of blocks (sub-images). Support Vector Machine (SVM) is used to classify mass or normal ROIs. The evaluation on DDSM, a benchmark mammograms database, revealed that localised DRLBP-HOG with 9 (3×3) blocks forms the best representation and yields an accuracy of 99.80 ± 0.62(ACC$\pm$STD) outperforming the state-of-the-art methods.

1 Introduction

The statistics reported by the American Cancer Society show that 246,660 new breast cancer cases and 40,890 deaths are expected in 2016, breast cancer alone is expected to account for 29% of all new cancer cases among women[1]. According to a report by King Faisal Specialist Hospital and Research Centre in Riyadh, the number of new cancer cases in Saudi Arabia has increased by more than 25% in the past 15 years, and is expected to rise considerably in the future. At 15% of the total number of cancers, breast cancer is the most common cancer type, followed by colorectal cancer with the share of 10.4% [2]. One of the main symptoms of breast cancer is the presence of masses in the breast. The studies have proven that the early detection of cancer would increase the life expectancy of the patients [1].

A mammogram is the most effective imaging modality for early breast cancer detection. However, computer aided diagnosis of masses with mammograms is a challenging task. About 95% of the 10% of women, whose mammogram is found to be abnormal, do not have cancer i.e. the number of false positives is high [1]. Many techniques have been proposed to overcome this problem. The efficiency and robustness of any technique depend on how effective is it in representing the micro-structures of ROIs. Recently, texture [3], [4],[5],[6],[7] and gradient orientation based [8] descriptors have been employed separately to represent ROIs and their performances indicate that both texture and gradient orientation micropatterns play important role in the discrimination of ROIs. As such, the fusion of texture and gradient orientation based descriptors can result in a more effective and robust description of ROI. Based on this idea, we propose new descriptors DRLBP-HOG and DRLTP-HOG by fusing DRLBP and DRLTP, which are stat-of-the-art best texture descriptors, and HOG, which is one of the best descriptor for gradient orientation patterns. Different micro-patterns exit at different locations in an ROI and to take into account their location is also important. We incorporate location information by dividing an ROI into a number of blocks (sub-images), thus computing localised DRLBP-HOG and DRLTP-HOG descriptors, which effectively capture the discriminative information of ROIs. For classification, we used SVM, and evaluated the proposed descriptors using DDSM, a benchmark database. Our method outperforms the state-of-the-art methods by giving an accuracy of 99.80 ± 0.6201.

The organization of the rest of the paper is as follows. In the next section, we give an overview of the stat-of-the-art techniques for false positive reduction. In Section 3, the methodology has been described in detail. Section 4 presents the results and discussion. Section 5 concludes the paper with future work.

2 Related work

In this section, first we present an overview of the recent work related to texture description and then we briefly review the recent methods which have been proposed for false positive reduction in mammogram based Computer Aided Diagnosis (CAD) systems for masses. We will focuss mainly on those techniques which employ different texture descriptors and gradient orientation for the the representation of ROIs.

Local Binary Pattern (LBP) [9] and Local Ternary Pattern (LTP) are two state-of-the-art local texture features, which have given promising performance results in many recognition and detection problems [3]. Both LBP and LTP suffer from the problem of brightness reversal of object and background i.e, they treat differently the bright object against a dark background and dark object against a bright background. Also, they do not differentiate between local patterns having weak contrast and those with strong contrast. To overcome these issues associated with LBP and LTP, Amit at el. [10] proposed Discriminative Robust Local Binary Pattern (DRLBP) and Discriminative Robust Local Ternary Pattern (DRLTP). Both DRLBP and DRLTP incorporate texture and edge information and are robust against the problem of the brightness reversal of object and background. Also, they discriminate between weak contrast and strong contrast local patterns.

Different types of texture features have been used to describe suspicious ROIs for false positive reduction. Llad et al. [3] proposed a new approach for false positive reduction. For the description of ROIs, they used localised LBP descriptor to differentiate true masses and normal parenchyma. First, they divide each ROI into blocks, extract LBP codes from each block, compute histogram of LBP codes, and finally concatenate the histograms corresponding to all blocks to form the descriptor. They used SVM for classification. This method yielded AUC of 0.94 on DDSM database.

Employing co-occurrence matrix and optical density transformation, Shen-Chuan et al. [11] proposed two complex descriptors, which describe local texture and the discrete photometric distribution of ROIs. For discriminating abnormal ROIs from normal ones, they used stepwise linear discriminant analysis, where decision is taken by selecting and rating the individual performance of each feature. The performance of this method in terms of area under ROC (AUC) is 0.98.

Abdel-Nasser et al. [6] proposed uniform local directional pattern (ULDP) descriptor for feature extraction from ROIs. This descriptor encodes the neighborhood of a pixel in an ROI based on its edge responses and spatial information. The histogram of ULDP forms the descriptor of an ROI and characterizes breast masses as well as different tissues in the breast. With SVM as classification technique, the performance of this method on MIAS database is 0.93 in terms of AUC.

Oliveira et al. [5] addressed the problem of the discrimination of ROIs as mass and non-mass using SVM. For the description of ROIs, they employed two types of texture features: taxonomic diversity index and taxonomic distinctness. They used logarithmic non-linear contrast enhancement to improve the quality of the regions and a mean filter mask to eliminate small structures from ROIs. The performance of this method on DDSM database is 98.8% in terms of accuracy.

Liu et al. [12] used texture features extracted employing gray level co-occurrence matrix (GLCM) and completed local binary pattern (CLBP) for the description of ROIs in their automatic mass detection method. They used support vector machine (SVM) to classify ROIs whether non-masses or masses. The performance results in this paper are given in terms of sensitivity and specificity, the results show that there is significant reduction if false positives.

Employing Gabor filters optimised with particle swarm optimization (PSO) technique for texture feature description from ROIs, Salabat et al. [13] proposed a false positive reduction method, which uses SVM for classification. This method archived an accuracy of 98.82% on DDSM database.

Pomponiu et al. [8] proposed an approach based on histogram of oriented gradients (HOG) for decreasing mass false positives by a computer aided detection (CAD) system. After describing ROIs using HOG, they classify them to identify mass and non-mass with support vector machine (SVM).

Different texture features and gradient orientation separately have been used for the description of ROIs and have shown promising results. Employing stat-of-the-art best texture descriptors DRLBP and DRLTP and gradient orientation based features such as HOG, we propose new descriptors for ROI description, which are more effective in the discrimination of mass and non-mass tissues.

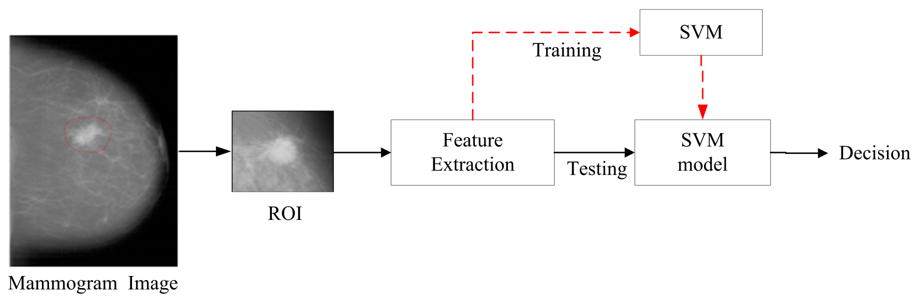

Fig. 1. An overview of false positive reduction method

3 Methodology

In computer aided diagnosis of masses in mammograms, suspicious mass regions are extracted from a mammogram; these ROIs may be true masses or normal tissues, which have been falsely identified as masses (false positives). The false positive reduction problem is to identify whether a suspicious ROI is a mass or normal tissue and it is a classification problem involving two classes (mass or normal tissue). An overview of the proposed method for false positive reduction is shown in Figure 1. The main steps in this method are an ROI description and SVM, a classifier. Classification performance depends on how much discriminatory is the description of ROIs. We propose two techniques for ROI description in the next subsection.

3.1 Feature extraction

Texture and gradient orientation patterns in a mammogram play important role in the discrimination of masses from normal parenchyma. Capturing these patterns effectively can lead to a discriminative description of ROIs, which result in small intra-class variation and large inter-class variation. In this section, we propose two descriptors which effectively encode texture and gradient orientation patterns.

LBP [9] is a local feature that is commonly used for texture description and has shown promising performance in many applications. LBP code of each pixel in an image is computed using a neighborhood (P, R), where P is the number of neighbors and R is the radius of the neighborhood. The intensities of the neighbors are converted into bits by thresholding them with the intensity value of the central pixel and a binary code is formed, which is the LBP code of the central pixel. LBP codes of all pixels are calculated and the histogram of these codes is computed, which is an LBP description of the image. There are four variants of LBP: simple LBP (LBP), uniform LBP (LBP^u), rotation invariant LBP (LBP^{ri}) and uniform rotation invariant LBP (LBP^{uri}). We tested all variants and found that (LBP^u) gives the best results among all variants of LBP. It is robust to illumination and contrast variations, but sensitive to noise, small pixel fluctuations and does not differentiate between weak and strong contrast [10]. To overcome the drawbacks of LBP, Satpathy et al. [10] proposed DRLBP. In LBP descriptor, uniform weights are given to LBP codes while binning them into the histogram irrespective of whether an LBP pattern has a weak contrast or strong contrast. To account for the contrast of an LBP pattern, an LBP code is weighted by the corresponding pixel gradient magnitude before binning into the histogram. The resulting descriptor is called Discriminative Robust Local Binary Pattern (DRLBP). It is invariant to changes of contrast and shape, and is more suitable for capturing texture patterns of breast masses, which involve changes in contrast and shape. Note that DRLBP involves gradient magnitude to weight LBP codes according to their local contrast edge micro-patterns, but does not employ gradient orientation and so it does not encode the gradient orientation patterns, which are also important for the discrimination of mass ROIs. Pomponiu et al. [8] have shown its effectiveness. We use HOG [15] to represent gradient orientation patterns.

HOG descriptor is computed as the histogram of gradient directions or edge orientations over the pixels, and thus it captures the gradient orientations patterns. It has excellent performance in many pattern recognition tasks including effective decrease in mass false positives for Computer aided diagnosis [8]. Fusing DRLBP and HOG, we compute DRLBP-HOG descriptor, which is robust in capturing texture edge micropatterns under illumination as well as contrast variations and gradient orientation patterns.

Local Ternary Pattern (LTP) is a variant of LBP, which is robust against noise. Similar to DRLBP, Discriminative Robust Local Ternary Pattern (DRLTP) descriptor is computed that is robust against illumination, contrast and shape changes [10]. Fusing DRLTP and HOG, we calculate DRLTP-HOG descriptor, which effectively represents the discriminative content of mass ROIs.

Note that DRLBP-HOG and DRLTP-HOG accumulate local edge micropatterns and gradient orientation patterns occurring at different locations, thus giving their global distributions, which do not take into account the fine local structural detail. To determine the local distributions of DRLBP-HOG and DRLTP-HOG descriptors for capturing the final local structural detail, we divide each ROI into a number of blocks, compute DRLBP-HOG and DRLTP-

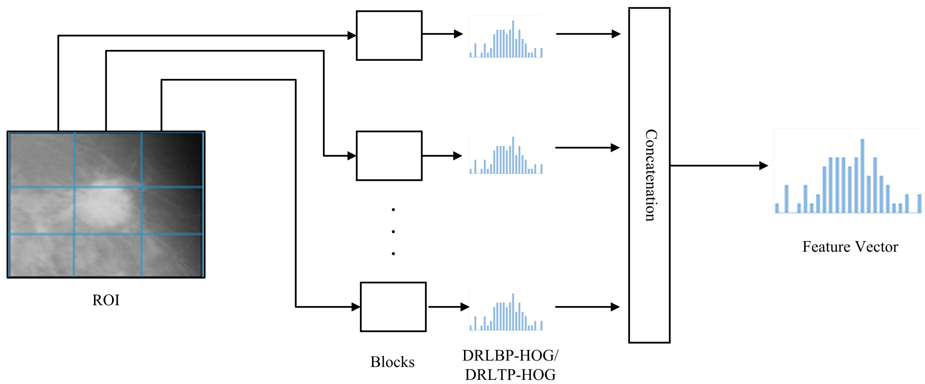

Fig. 2. The detail of extracting localised DRLBP-HOG and DRLTP-HOG descriptors

HOG descriptors from each block and then concatenate them to form localised DRLBP-HOG and DRLTP-HOG descriptors, Figure 2 shows this process.

3.2 Classification

False positive reduction is a two class classification problem and it has been shown that for this problem, SVM outperforms other classifiers like multilayer perception (MLP)[16]. The SVM performs classification task by constructing optimal hyperplane with maximum margin in a multidimensional space that separates regions belonging to the two classes [17]. SVM is a linear classier but in general the space of DRLBP-HOG and DRLTP-HOG features is not linearly separable. The solution is kernel trick, which transforms the original space to a higher dimensional space where the original space becomes linearly separable. As the Radial Basis Function (RBF) kernel has shown promising results in mass classification, so we employ RBF kernel. SVM with RBF kernel involves two parameters: σ, the width of RBF kernel and C, the soft margin parameter. Using training data, ten-fold cross-validation, and loose and fine grid search, the optimal values of these parameters are calculated [16].

4 Result and Discussion

In this section we present the results and discuss them. For the validation of the proposed method, we test it using 512 ROIs taken from Digital Database for Screening Mammography (DDSM)[11] using the annotation of each case selecting the cases which are not obvious. Half of these ROIs are normal, but look like mass ROIs, some sample ROIs have been shown in Figure 3.

The proposed method involves several parameters: σ, the width of RBF kernel, C, the soft margin parameter,the number of blocks for the division of an ROI, and the number of bins in HOG. The first two parameters are related to

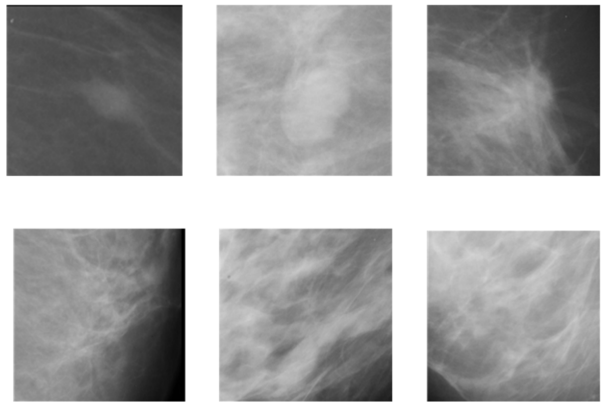

Fig. 3. Top Row Mass ROIs, Bottom Row Normal ROIs

SVM and are tuned using the method described in Section II. We divided ROIs into numbers of blocks N×N, N = 3, 4 and 5 i.e. 9, 16 and 25 blocks to find the best division. For the computation of DRLBP, we used uniform LBP and found that HOG with 32 bins gives the best result. For performance evaluation, we employed ten-fold cross-validation procedure, where a dataset is divided into 10 folds of equal sizes, one fold at a time is held out for testing and the remaining folds are used to train the classifier; a performance measure is computed as an average over ten-folds along with standard deviation (STD). In this way, the system is trained with different data and is tested with different data, which has not been shown to the system during training, avoiding over-fitting. We measured the performance using common performance metrics: accuracy (ACC), area under the ROC Curve (AUC), Sensitivity (SN), and Specificity (SP).

To validate the effectiveness of DRLBP-HOG and DRLTP-HOG descriptors, we also evaluated HOG, DRLBP and DRLTP separately; the results are shown in Table I, which indicate that 25 blocks give an overall good performance in terms of the four measures. HOG gives better result than DRLBP and DRLTP, which means that gradient orientation pattern have a dominant role in the discrimination of mass ROIs. For localised LBP-HOG, DRLBP-HOG and DRLTP-HOG descriptors, we tested 9, 16 and 25 blocks and found that 9 blocks give the best performance; the results are given in Table 2. There is significant improvement in the results, which implies that our assumption about the edge micro-patterns and gradient orientation is justified. Also, notice that LBP-HOG does not improve the results over HOG, and DRLBP-HOG yields the best performance in terms of all four metrics, especially the sensitivity is 100%.

ROC curves illustrate the performance on a binary classification problem where classification is based on simply thresholding a set of scores at varying levels. It shows the tradeoff between sensitivity and specificity, any increase in sensitivity will be accompanied by a decrease in specificity. For the cases, whose results are shown in Table 2, ROC curves are shown in Figure 4, which reflect the performance of the system in terms of sensitivity and specificity.

Table 1. Average performance measures with a standard deviation for three descriptors

Method	#Blocks	ACC±STD	AUC±STD	SN±STD	SP±STD
HOG	9	91.76±3.17	0.91±0.04	92.15±4.16	91.55±6.53
	16	92.15±2.06	0.92±0.03	90.91±4.40	93.33±3.36
	25	92.35±2.84	0.92±0.04	0.91±0.04	92.73±4.22
DRLBP	9	80.58±4.57	0.80±0.05	79.28±5.19	81.61±6.55
	16	81.56±4.35	0.79±0.08	79.95±9.04	81.66±11.26
	25	82.64±5.37	0.81±0.06	79.55±7.28	85.10±8.60
DRLTP	9	79.02±4.03	0.78±0.05	76.57±5.86	80.97±7.12
	16	82.35±4.23	0.81±0.07	82.11±6.60	81.62±10.05
	25	82.35±4.89	0.81±0.05	9.15±6.72	84.77±8.78

Table 2. Average performance measures with standard deviation for LBP-HOG, DRLBP-HOG and DRLTP-HOG descriptors

Method	#Blocks	ACC±STD	AUC±STD	SN±STD	SP±STD
LBP+HOG	9	91.57±2.93	0.86±0.02	79.76±5.44	95.26±±3.56
DRLBP+HOG	9	99.80±0.62	0.99±0.01	100±0	99.80±1.21
DRLTP+HOG	9	98.23±1.71	0.98±0.02	98.52±2.41	98.0847±2.72

Table 3. Comparison with state-of-the-art false positive reduction methods

Method	Year	Dataset	ACC(%)	AUC
DRLBP-HOG (Proposed)	2016	DDSM	**99.80**	**0.99**
Salabat et al. [13]	2016	DDSM	98.82	0.99
Oliveira et al. [5]	2015	DDSM	98.88	
Salabat et al. [7]	2015	DDSM	98.02	0.96
Tai et al. [18]	2014	DDSM		0.98
Hussain [4]	2014	DDSM	98.93	0.99

A comparison with state-of-the-art methods is given in Table 3. We made comparison with those recent methods which employ texture descriptors other than LBP and DDSM for evaluation; it shows that the proposed method (DRLBP-HOG with SVM) outperforms in false positive reduction method on average in terms of accuracy and AUC.

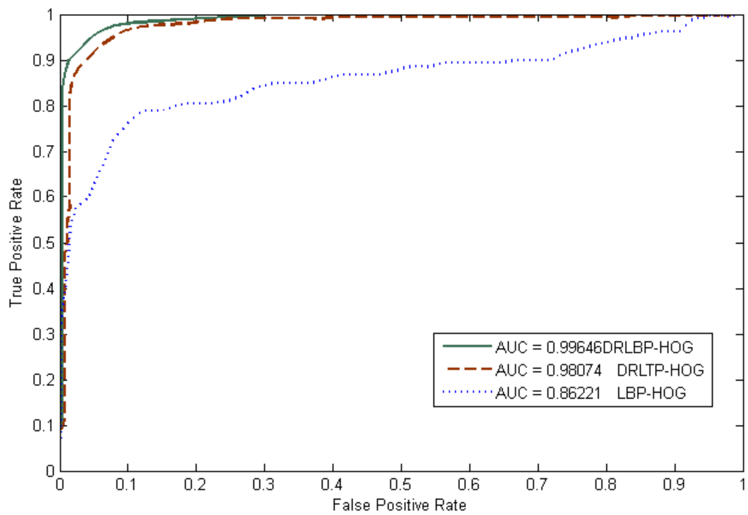

Fig. 4. ROC curve of the outperformance descriptors

5 Conclusion and Future Work

The false positive reduction problem is a challenging problem, and the effectiveness of any method addressing this problem depends on how effectively it extracts the discriminative information from an ROI. Assuming that an ROI contains texture micropatterns with varying contrast and gradient orientation patterns, we proposed two descriptors DRLBP-HOG and DRLTP-HOG by fusing DRLBP, DRLTP which capture texture patterns and HOG which encodes gradient orientation patterns. For localised distribution of these descriptors, we divided an ROI into a number of blocks. The experiments on ROIs from DDSM database revealed that DRLBP-HOG with 9 blocks and 30 bins of HOG give the best performance, which is better that those by recent method. The results corroborate our assumption and this can further be utilised to classify the mammograms based on density and also for the classification of benign and malignant masses. This is our future work.

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