COMPUTER AIDED DETECTION AND DIAGNOSIS IN MAMMOGRAPHY

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ABSTRACT: Screening mammography is the most effective tool for early detection of breast cancer. In this procedure, radiologists scan x-ray images of the breast to locate signs of breast cancer. However it is not perfect and has low sensitivity for detection and low specificity for diagnosis. Various computer aided detection (CAD) and diagnosis (CADx) systems have been developed to aid radiologists. In this paper, we present two studies aimed at improving the performance of existing CAD and CADx algorithms. In the first study, we present a novel evidence based, stage-one algorithm for the detection of spiculated masses (SM) and architectural distortions (AD). By evidence based, we mean that we use the statistics of the physical characteristics of these abnormalities to determine the parameters of the detection algorithm. Each parameter of the algorithm has been incorporated to capture the variation in physical characteristics of SM and AD. The second study is aimed at improving the performance of current diagnosis systems by combining information from multiple views. It is designed to look at the correspondence of features from multiple views. It tires to address the fundamental issue of whether using data from multiple views can really provide additional insight to the diagnosis problem.

INTRODUCTION & BACKGROUND: The American Cancer Society estimates that 211,240 women will be diagnosed with breast cancer in the U.S. in 2005[1]. In the US, breast cancer is the most common form of cancer among women and is the second leading cause of cancer deaths, after lung cancer [1]. Early detection of breast cancer increases the survival rate and increases the treatment options.

Screening mammography, x-ray imaging of the breast, is currently the most effective tool for early detection of breast cancer. Screening mammographic examinations are performed on asymptomatic woman to detect early, clinically unsuspected breast cancer. Two views of each breast are recorded; the craniocaudal (CC) view, which is a top to bottom view, and a mediolateral oblique (MLO) view, which is a side view taken at an angle. Examples of the MLO and CC views are shown in Figure 1.

Radiologists visually search mammograms for specific abnormalities. Some of the important signs of breast cancer that radiologists look for are clusters of microcalcifications, masses, and architectural distortions. A mass is defined as a space-occupying lesion seen in at least two different projections[3]. Calcifications are tiny deposits of calcium, which appear as small bright spots on the mammogram. Architectural distortions are defined as follows, “The normal architecture is distorted with no definite mass visible”[3]. A typical example of each of these abnormalities is shown in Figure 2.

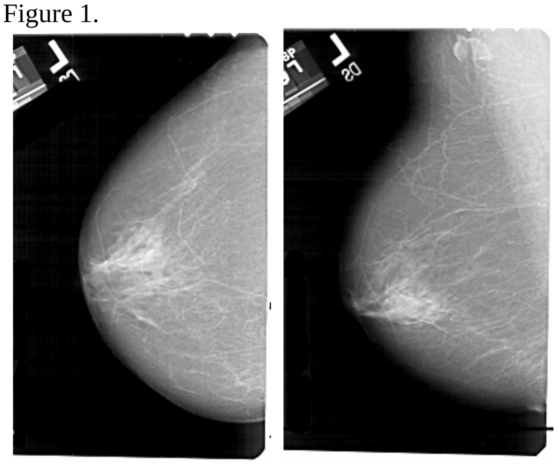

Figure 1. The craniocaudal (CC) view (left) and a mediolateral oblique (MLO) view (right).

Breast lesions are described in terms of their shape, margin and distribution characteristics. These characteristics are reported according to the Breast Imaging Reporting and Data System (BI-RADS™) [3]. BI-RADS™ is a mammography lexicon developed by the American College of Radiology (ACR), for the description of mammographic lesions.

Early detection via mammography increases breast cancer treatment options and the survival rate[4]. However, mammography is not perfect. Detection of suspicious abnormalities is a repetitive and fatiguing task. As a result, radiologists fail to detect 10-30% of cancers[5], approximately two-thirds of which are evident retrospectively[6]. Mammography has a positive predictive value (PPV) of less than 35% [7], where the PPV is

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defined as the percentage of lesions subjected to biopsy that were found to be cancer. Thus, a high proportion of biopsies are performed on benign lesions. Avoiding benign biopsies would spare women anxiety, discomfort, and expense.

Computer-Aided Detection (CAD) systems have been developed to aid radiologists in detecting mammographic lesions that may indicate the presence of breast cancer. These systems act only as a second reader and the radiologist makes the final decision. Recent studies have also shown that CAD detection systems, when used as an aid, have improved radiologists' accuracy of detection of breast cancer [8]. Computer-Aided Diagnosis (CADx) systems for aiding in the decision between follow-up and biopsy are still in development. CAD/CADx systems either use features extracted by human observers (*e.g.* BI-RADS™ descriptors) or features extracted directly from digitized/digital mammograms using image processing techniques (*e.g.* texture features, statistical moments).

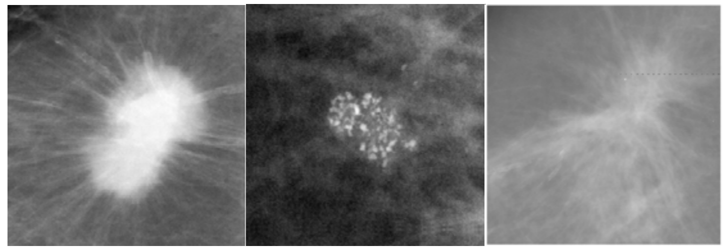

Figure 2. Examples of a spiculated mass (left), cluster of microcalcifications (center), and architectural distortion (right).

The paper describes two studies related to CAD/CADx of breast cancer using mammography images. The first one is a novel technique for the automatic detection of spiculated masses and architectural distortions. The second studies the correspondence between human extracted BI-RADS™ features and computer extracted image texture features. This information would be useful in designing classifiers that use information from both views for diagnosis of lesions.

MATERIALS: The images for the studies described in this paper were obtained from the Digital Database for Screening Mammography (DDSM)[2]. The DDSM is the largest publicly available data-set of digitized mammograms. It contains 2620 cases acquired from multiple medical institutions.

A. Evidence-based detection of spiculated masses and architectural distortions

Purpose: The purpose of this study was to develop a new method for the detection of spiculated masses (SM) and architectural distortions (AD) based on their physical characteristics.

Motivation: We focused on the detection of SM and AD for a number of reasons. SM carry a much higher risk of malignancy than calcifications or other types of masses. About 81% of SM[9] and 48-60% of AD are malignant [10]. It is estimated that 12-45% of cancers missed in mammographic screening are AD [11]. The detection sensitivity of the current CAD systems for SM and AD is low and there is a pressing need for improvements in their detection.

Methods: Most mass detection algorithms consist of two stages. The aim of the first stage is to detect all potential masses. In the second stage, the aim is to reduce the false-positives by classifying the detected masses as true masses or normal tissue. Our stage-one algorithm consists of two steps, an enhancement step followed by a filtering step. In the first step, we propose a new technique for the enhancement of spiculations in which a linear filter is applied to the Radon transform of the image. The filter parameters were set based on measurements made on a set of spiculated masses. The width of spiculations was measured manually by a graduate student and an experienced radiologist. In the second step, we filtered the enhanced images with a new class of linear image filters called 'Radial Spiculation Filters'. Two such filter-banks are shown in the Figure 3. We have invented these filters specifically for detecting spiculated masses and architectural distortions characterized by converging lines or spiculations. A key aspect of this work is that each parameter of the filter has been incorporated in the filter design to capture the great variation in the physical characteristics of spiculated masses and architectural distortions. To evaluate the performance of the detection algorithm, two sets of images were

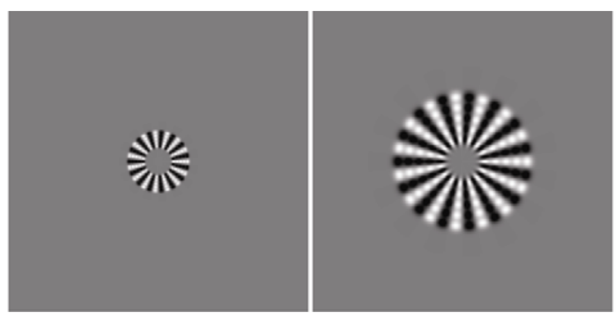

Figure 3: Radial Spiculation Filters: A new class of filters we have developed for the detection of SM and AD. The figures above show two sets of filter-banks for specific parameter values.

used. One set contained 45 images with SM and the other set contained 45 images with AD. These images were scanned with a single digitizer and contained a single lesion and were randomly selected.

Results: The detection results of the algorithm are shown in Figure 4. This figure shows the FROC curves for the detection of spiculated masses and architectural distortions. We achieved a sensitivity of 78% at 10 FPI for architectural distortions and 98% at 14 FPI for spiculated masses. These results are competitive with existing stage-one algorithms. We are also developing a stage-two algorithm to reduce the number of FPI.

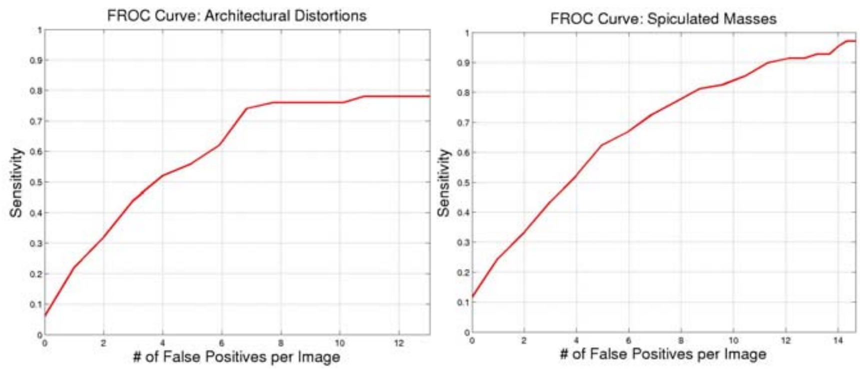

Fig. 4 FROC curves for the stage-one detection algorithm.

New or breakthrough work: To the best of our knowledge, no prior studies have attempted to use the statistics of the physical characteristics of spiculated masses and architectural distortions to guide the design and development of a detection algorithm.

Conclusions: A new evidence based method was developed for stage one of the detection of spiculated masses and architectural distortions. Further details can be found in [12].

B. Correspondence in BI-RADS™ Descriptors and Texture Features between Mammographic Views

Purpose: The purpose of this study was to assess the agreement of human extracted BI-RADS™ lesion descriptors from the MLO and CC mammographic views. The correlation between image texture features derived from the two views was also studied.

Motivation: Radiologists routinely use multiple mammographic views for detection and diagnosis. This improves performance relative to using a single view[13]. It is likely that CAD/CADx algorithms could also benefit from the use of information from multiple views. However, it would be redundant to use two mammographic views in CAD/CADx if they provide the same information. This provides the motivation to study the correspondence between features from the MLO and CC views of the breast.

Methods: Using kappa statistics[14], the amount of variation in the reported categories of the BI-RADS™ descriptors, BI-RADS™ assessment, and subtlety ratings for the two views was assessed for 1626 cases from the DDSM. This analysis was stratified by lesion type, pathology outcome, and institutional source of data. Mass cases with low agreement between views were identified. These were used to design linear discriminant analysis (LDA) based classifiers that combined BI-RADS™ information from the two views. The impact of the addition of patient age as a feature on the classifier performance was also assessed.

The correlation between thirteen Haralick's texture features extracted from the MLO and CC mammographic views of breast lesions was also studied. Features were ranked on the basis of correlation values. The two-view correlation of features for masses was compared against that for calcifications. A similar comparison was done for benign and malignant lesions.

Results: The agreement between the BI-RADS™ descriptors from the two views was consistently higher for calcifications as compared to masses. The agreement also depended on the institutional source of the data presumably due to differences in interpretation of instruction given to read mammograms at the different institutions. A classifier that used patient age and averaged the results of two LDA classifiers trained separately on the MLO and the CC views displayed the best performance with the highest area under the ROC curve (AUC ± SD = 0.927 ± 0.026). This is depicted as the classifier AVERAGE in Figure 5.

Correlation coefficient values of texture features from the two views varied from 0.4 to 0.8. Of the thirteen texture features some were more correlated than the others. Significant differences were found between the correlation of Haralick's texture features from the two views for different lesion types and lesion pathologies. It was observed that the texture features from the MLO and CC views were less strongly correlated for calcification lesions than for mass lesions. Similarly, texture features from the two views were less strongly correlated for benign lesions than for malignant lesions.

New or Breakthrough work: This study is novel in the sense that it addressed for the first time the question of whether an additional mammographic view really adds to information from the existing view or is merely a replication of it's information. This is fundamental in building CADx systems based on multi-view information.

Conclusions: The correspondence studies suggest that combining dissimilar information from multiple mammographic views may hold potential to improve the performance of CADx systems.

CONCLUSIONS: In this paper we have summarized the work carried out in the area of CAD and CADx at the Laboratory for Image and Video Processing (www.live.ece.utexas.edu) and the Biomedical Informatics Laboratory (www.bme.utexas.edu/research/informatics/). It is important to realize that mammographic image analysis is an extremely challenging task for a number of reasons. First, since the efficacy of CAD/CADx systems can have very serious implications, there is a need for near perfection. Second, the large variability in the appearance of abnormalities makes this a very difficult image analysis task. Finally, abnormalities are often occluded or hidden in dense breast tissue, which makes detection difficult. We are currently working on the improving the CAD and CADx algorithms we have developed.

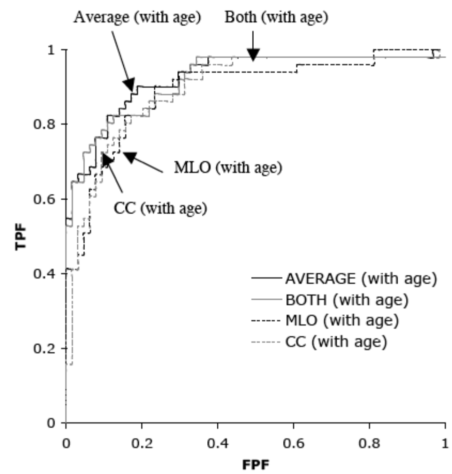

Figure 5: ROC curves depicting the performance of the classifiers MLO (with age), MAXIMUM (with age), AVERAGE (with age) and BOTH (with age).

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