Latest Advances in Computer-Aided Detection of Breast Cancer by Mammography

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ABSTRACT

Breast cancer is detected to be the second deadliest cancer among the cancerous woman society. Statistical data shows that the trend is increasing every year. Early detection and removal of the cancerous part is the most effective way to cure a cancer. Computer-aided-detection (CAD) system can plays a vital-role in the early detection of breast cancer and can reduce the death rate among women with breast cancer. This paper aims to provide an overview of recent advances in the development of CAD systems and related techniques. Primarily we begin with a detailed introduction of some basic concepts related to breast cancer detection and diagnosis, then focus on the key CAD techniques developed recently for breast cancer, including detection of masses, calcification, architectural distortion, bilateral asymmetry in mammograms.

***Index Terms*— Computer-aided-detection, Breast cancer, Mammography.**

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I. INTRODUCTION

In recent times, breast cancer is found to be the most frequent form of cancer in women, especially in the western part of the world. The use of mammography as a screening tool for the detection of early breast cancer in otherwise healthy women without symptoms continues to be debated. Critic point out that a large number of women need to be screened to locate cancer. The death rate from breast cancer has decreased by almost 30% and points to studies in Sweden and the Netherlands that show two-thirds of the decrease in cancer deaths is due to mammography screening. There is clear evidence which shows that early diagnosis and treatment of breast cancer can significantly increase the chance of survival for patients [1]–[4]. The earlier the cancer is detected, better the chances that a proper treatment can be arranged. At present, there are no effective ways to prevent breast cancer, because its cause remains unidentified. However, efficient identification of breast cancer in its early stages can give a woman a better chance of full improvement. Therefore, early detection of breast cancer can play an important role in reducing the associated morbidity and death rates.

Computer-aided diagnosis is a system specifically planned to spot abnormalities in mammograms such as calcification, masses and architectural distortion and aid the radiologist in detecting apprehensive areas on the mammograms. According to American Cancer Society (ACS), some studies have shown that Computer-aided-detection can help to locate cancers. For research scientists, there are more than a few interesting research topics in cancer detection and diagnosis system, such as high-efficiency, high-accuracy lesion detection algorithms, including the detection of masses, calcification, architectural distortion, and bilateral asymmetry in mammograms. On the other hand, there are strong motivations to develop a CAD system to assist radiologists in understanding mammograms.

This paper presents a general idea of CAD systems and related techniques developed in recent years. It is also intended to draw the concentration of more research scientists to the research field of CAD for breast cancer, and progress research on the detection and identification of breast cancer and related techniques, such as image processing, radiological imaging, and computer expertise.

The remaining part of the paper is organized as follows. Section II, evaluates the key techniques used in CAD systems for breast cancer, including many newly developed algorithms for detection of masses, calcification, architectural distortion and bilateral asymmetry in mammograms. Section III, talks about the issues related to the future of CAD systems for breast cancer and section IV concludes the paper.

II. KEY TECHNIQUES FOR CAD SYSTEMS

Even though many techniques have been put forth so far, the growth of new algorithms for Computer-aided-detection of breast cancer is still an active research field, predominantly in regard to the detection of subtle abnormalities in mammograms [20]. In this section, different techniques for the detection of masses, calcification, architectural distortion, bilateral asymmetry in mammograms is reviewed.

A. Detection of microcalcification MC Clusters in Mammograms.

Microcalcifications, one of the premature indicators of breast cancer, are tiny granule-like deposits of calcium as shown in Fig (1). The occurrence of clustered microcalcifications in X-ray mammograms is an important display for the detection of breast cancer, particularly for individual microcalcifications with diameters of about 0.7 mm and with an average diameter of 0.3mm[5].Radiologists describe a cluster of microcalcifications as the occurrence of three or more visible microcalcifications within a square centimeter region of the mammogram [5].The detection of clustered microcalcifications in mammograms has been of great interest to many researchers [6]–[15]. MC detection methods could be broadly separated into the following four categories: 1) basic image enhancement methods; 2) stochastic modeling methods; 3) multiscale decomposition methods; and 4) machine learning methods.

Multiscale decomposition methods aims to develop a computerized format based on wavelet transform, a robust tool for image analysis, enhancement, and pattern recognition [16], [17]. Wavelet transform is basically a filtering technique that represents images hierarchically on the basis of scale or resolution. It moreover provides a powerful method for analyzing high-spatial- frequency phenomena restricted to a small area in space, and, thus, can efficiently extract information derived from localized high-frequency signals, such as those emitted by microcalcifications. Nakayama *et al* [18] developed a computerized scheme for detecting early-stage microcalcification clusters in mammograms. It developed a novel filter bank based on the idea of the Hessian matrix for classifying nodular structures and linear structures. The mammogram imagery was decomposed into a number of sub images for following difference at scales from 1 to 4 by this filter bank. The sub images for the nodular component (NC) and the sub images for the nodular and linear component (NLC) are then obtain from study of the Hessian matrix. Many regions of interest (ROIs) were chosen from the mammogram image. In every ROI, eight features were determined from the sub images for NC at scales starting 1 to 4 and the sub images for NLC at scales from 1 to 4. The

Bayes discriminant function was working for unique among abnormal ROIs with a microcalcification cluster and two unlike types of normal ROIs without a microcalcification cluster.

The evaluation detection is show by means of 600 mammograms. The computerized scheme was revealed to have the potential to detect microcalcification clusters with a clinically suitable sensitivity and low false positives. In order to train and estimate this computerized scheme, we divided our database into a training set and a test set. Each set built-on 600 mammograms obtained from 150 patients. The entire number of microcalcification clusters was 300 in the training set, and 310 in the test set. The ROIs at intervals of 23 pixels (approximately 1 mm) were chosen, so that one ROI would go beyond with the neighboring ROIs. The training is made using Bayes discriminant function by using three different types of ROI selected from the training set. These ROIs were 300 abnormal ROIs by means of a microcalcification cluster, 300 normal ROIs with blood vessels, and 300 normal ROIs with no blood vessels. Abnormal ROIs were chosen so that the centers of microcalcification clusters would be synchronized with the centers of the ROIs. Normal ROIs were arbitrarily selected from normal mammograms that did not contain microcalcification clusters. The computerized scheme based on the Bayes discriminant function with eight features for distinguishing among three types of ROI identifies 310 of the 310 microcalcification clusters in the test set, yielding a sensitivity of 100.0% and a false positive rate of 0.98 per mammogram.

Machine learning methods intend to decipher dependencies from data. In the environment of MC detection, the problem is normally treated as a binary classification process, where the objective is to determine whether an MC is present or not at a pixel location. Liyang *et al.* [19] proposed several machine-learning methods for automated classification of clustered microcalcifications (MCs). The classifier is part of a computer- aided diagnosis (CAD) scheme that is meant to assisting radiologists in creation more accurate diagnosis of breast cancer on mammograms. The methods we consider were: Kernel Fisher Discriminant (KFD), Relevance Vector Machine (RVM), Support Vector Machine (SVM), and committee machines, of which most have been developed newly in statistical learning theory. Differentiation of malignant from benign MCs as a supervised learning problem has been formulated, and applied these learning methods to extend the classification algorithm. As input, these method used image features automatically extracted from clustered MCs. Testing these methods is done using a database of 697 clinical mammograms from 386 cases, which included a wide spectrum. Here receiver operating characteristic (ROC) analysis to calculate and to compare classification performance by the different methods. In addition, investigated how

to combine information from multiple-view mammograms of the same case so that the best decision can be made by a classifier. The kernel-based methods (i.e., SVM, KFD, and RVM) yielded the best performance (A_Z = 0.85, SVM), significantly outperforming a well-established, clinically-proven CAD approach that is based on neural network (A_Z = 0.80).

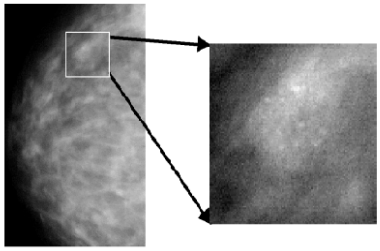

Fig. 1. Left: a CC view mammogram; right: expanded view showing clustered MCs. MCs is small granule-like deposits of calcium, and appear as bright spots in a mammogram.

B. Detection of Masses in Mammograms

A mass is defined as a space-occupying lesion seen in more than one projection [21]. A mass is regularly characterized by its shape and margin [20], [22]. In general, a mass with a normal shape has a higher probability of being benign, whereas a mass with an unequal shape has an advanced probability of being malignant as shown in Fig (2). Most of the mass detection algorithms are composed of two stages [20], [22]: 1) detection of suspicious regions on the mammogram and 2) classification of suspicious regions as mass or normal tissue. The algorithms for the first stage in mass detection are usually pixel-based or region-based [20], [21], [22]. In the pixel-based approaches, features are extracting for each pixel and classified as suspicious or normal [20]. The subsequent approach for mass detection is region-based [20]. In the region-based approach, ROIs are segmented, and then, features are extracted from each region, which are then used to classify the regions as suspicious or not suspicious.

Lubomir *et al.* [23] proposed a new type of classifier combining an unsupervised and a supervised model was intended and applied to classification of malignant and benign masses on mammograms. The unsupervised model is based on an adaptive resonance theory (ART2) system which clustered the masses into a numeral of separate classes. The classes were separated into two types: individual containing only malignant masses and the supplementary containing a mix of malignant and benign masses. The masses from the malignant classes are classified by ART2. The masses from the varied classes were input to a supervised linear discriminant classifier (LDA). In this method, some malignant masses were separated and classified by ART2 and the less distinguishable benign and malignant masses were classified by LDA. For

the estimate of classifier performance, 348 regions of interest (ROI's) contain biopsy proven masses (169 benign and 179 malignant) were used. Ten unlike partitions of training and test groups were generated at random using an average of 73% of ROI's for training and 27% for testing. The test group was kept self-determining of the training group. The hybrid classifier was compare to that of an LDA classifier alone and a back propagation neural network (BPN). Receiver operating characteristics (ROC) analysis was used to calculate the accuracy of the classifiers. The standard region under the ROC curvature (Az) for the hybrid classifier was 0.81 as evaluate to 0.78 for the LDA and 0.80 for the BPN. The incomplete areas above a true positive fraction of 0.9 were 0.34, 0.27 and 0.31 meant for the LDA and the BPN classifier, hybrid respectively. These outcomes specify that the hybrid classifier is a promising approach for improving the correctness of classification in CAD applications [23].

Pelin *et al.* [24] proposed a decision making that performed in two stages as feature extraction by computing the wavelet coefficients and classification using the classifier trained on the extracted features. Support Vector Machine (SVM), a learning machine based on statistical learning theory, is trained during supervised learning to classify masses. It involved 66 digitized mammographic images. The masses are segmented manually by radiologists, previously to introduction to the classification system. Beginning test on mammogram show over 84.8% classification accurateness by using the SVM with Radial Basis Function (RBF) kernel. In addition confusion accuracy, specificity sensitivity, and matrix analysis with dissimilar kernel types were used to illustrate the classification performance of SVM [24].

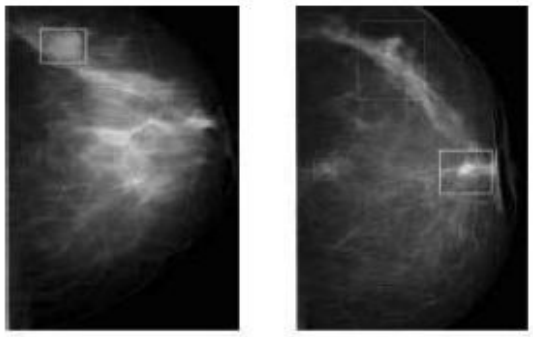

Fig. 2. A Sample Mammographic Image from Our Data Set

C. Detection of Architectural Distortion in Mammograms

The normal architecture (of the breast) is distorted with no definite mass visible. This includes speculations radiating from a point and focal retraction at the edge of the parenchyma. Architectural distortion is able to also be an associated finding as shown in Fig (3). Architectural distortion is the third most general mammographic sign of nonpalpable breast cancer [25], [26], but due to its subtlety and

changeable presentation, it is often missed during screening. Architectural distortion accounts for 12%–45% of breast cancers unnoticed in screening mammography [27], [28].

Sujoy *et al.* [29] proposed a generative model for constructing an efficient set of unique textures for recognizing architectural distortion in digital mammograms. In the primary layer of the proposed two-layer architecture, the mammogram is examine by a multiscale oriented filter bank to appear as a texture descriptor of vectorized filter responses. It presumes that every mammogram can be characterize by a carrier of primitive texture patterns and the set of textural primitives is represented by a mixture of Gaussians which builds up the second layer of the proposed model. The experimental textural descriptor in the first layer is assumed to be a stochastic realization of one or more textural primitive from the second layer. The result obtained on two openly obtainable datasets, namely Mammographic Image Analysis Society (MIAS) and Digital Database for Screening Mammography (DDSM), show the efficiency of the anticipated approach.

Rangaraj *et al.* [30] proposed methods for the detection of sites of architectural distortion in prior mammograms of interval-cancer cases. It put forward that screening mammograms obtained earlier to the detection of cancer could contain subtle signs of premature stages of breast cancer, architectural distortion. The methods are based upon Gabor filters, a novel method for the examination of the fractal analysis, angular spread of power, Laws texture energy measures resulting from geometrically transformed regions of interest (ROIs), and Haralick's texture features. Among Gabor filters and phase portrait analysis, 4224 ROIs be automatically obtained from 106 prior mammograms of 56 interval-cancer cases, including 301 true-positive ROIs associated to architectural distortion, in addition to 52 mammograms of 13 normal cases. For every ROI, the entropy of the angular spread of power, the fractal dimension, 10 Law measures, and Haralick's 14 features were computed. The area less than the receiver operating characteristic curves obtained use the features chosen by stepwise logistic regression and the leave-one-ROI-out method are 0.75 with Fisher linear discriminant analysis, 0.76 with the Bayesian classifier and 0.78 with a single-layer feed-forward neural network. Free-response receiver operating uniqueness indicates sensitivities of 0.80 plus 0.90 at 5.8 plus 8.1 false positives per image, correspondingly with the Bayesian classifier and the leave-one-image-out method.

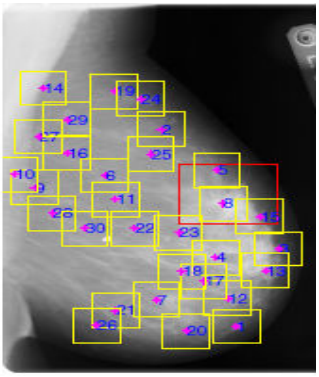

Fig. 3. A prior mammogram of an interval-cancer case with architectural distortion.

D. Detection of Bilateral Asymmetry in Mammograms

Asymmetry between the left and right mammograms of a specified subject is a main sign used by radiologists to diagnose breast cancer [30]. The BI-RADS [21] description of asymmetry indicates the occurrence of a greater density of breast tissue not including a distinct mass, in one breast as compare to the corresponding area in the other breast. Examination of asymmetry can give clues about the early signs of breast cancer, such as increasing densities, parenchymal distortion, and tiny asymmetric dense regions as shown in Fig (4). Nothing like for the detection and analysis of calcifications and masses, there are only a small number of publications on the detection of bilateral asymmetry in mammograms [25], [31], [32].

Ferrari *et al.* [33] proposed a method for the analysis of left–right (bilateral) asymmetry in mammograms. The method is based upon the detection of linear directional components by means of a multiresolution representation based upon Gabor wavelets. An exacting wavelet scheme with two-dimensional Gabor filters as elementary functions with changeable alteration frequency and orientation, purposely designed in order to decrease the redundancy in the wavelet-based illustration, is applied to the given image. The filter responses for various scales and orientation are analyzed by means of the Karhunen–Loeve (KL) transform and Otsu's method of thresholding. The KL transform is useful to select the principal components of the filter response, preserving only the most related directional elements appearing at all scales. The chosen principal components, threshold by with Otsu's method, used to get the magnitude and phase of the directional components of the image. A whole of 80 images from 20 normal cases, 14 asymmetric cases, and 6 architectural distortion cases from the Mini-MIAS (Mammographic Image Analysis Society) database were used to calculate the scheme using the leave-one-out methodology. Standard classification accuracy rates of up to 74.4% were achieved.

Jelena *et al.* [34] proposed detection of breast abnormalities in early stage of breast cancer development. One of the abnormalities that may specify breast cancer in its premature phase is bilateral asymmetry. It

presents computer-aided detection algorithm for bilateral asymmetry that uses B-spline interpolation for breast position. Alignment of the right and left breast is main step in computer-aided detection algorithm in order to permit comparison of resultant points in right and left breast. Differential investigation of breasts is based on simple subtraction technique. Is experienced on a set of 70 pairs of right and left MLO digital mammographic imagery, as of 70 different patients. All images are stored in compliance with DICOM standard. [35].

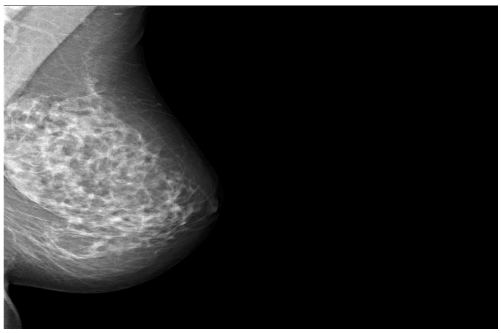

Fig. 4. Bilateral Asymmetry

III. DISCUSSION

Upcoming work on computer-aided breast cancer detection should focus on the consideration in improving the performance of CAD systems. Even though present CAD systems have not been fully doing well, we believe that advance studies on CAD systems and related technique should help develop their performance, and in this manner facilitate them to gain more widespread adoption in breast care clinics. For MC detection, the last two decades have witnessed a great number of MC detection algorithms developed for mammograms. In current years, several CAD systems that support MC detection have been deployed for clinical use. On the other hand, literature reports illustrate mixed outcome on the role of current CAD systems in practice, with some performance improvement and others showing no improvement.

Some of these systems may be likely to overemp assize the sensitivity in their detection ability at the cost of specificity. This, in a lot of cases, may end result in increased unnecessary biopsies when using such CAD systems. On the other hand, we feel that the problem of MC detection should not be simply treated as looking for “blobs” in an inhomogeneous image background; improved considerate of MC characteristics as perceived by expert should be well thought-out. In addition, different conditions of mammographic characteristics linked with X-ray exposure and breast tissue density should be studied across different institution. Having more civic datasets for evaluating the different detection techniques could help improved knowing the recent status of the field. In addition mammography, other imaging modalities for example magnetic resonance imaging and 3-D ultrasonography are currently being investigated in the

literature. Information from these imaging modalities could be of use for validating the ground fact used for current and new methods. Masses are further hard to discover than MCs because the features of a mass may be hidden by or be like to those of normal breast parenchyma. Accordingly, mass detection remains to be a noteworthy topic in breast cancer detection. As well mass detection, other main topics are the detection of architectural distortion and the detection of bilateral asymmetry in mammograms. At present, mutually the detection of architectural distortion and the detection of bilateral asymmetry in mammograms are important research topics, and well-organized solutions to these two issues could get better the performance of CAD systems.

IV. CONCLUSION

Computer-Aided-Detection (CAD) is a vital system for early detection of breast cancer. A noteworthy amount of work has been done in this area over the past 20 years. On the other hand, the performance of current CAD systems still needs improvement to fully meet up the requirements for everyday clinical applications. In the direction of an effective CAD system for breast cancer detection, many techniques have been developed. This paper has provided an outline of the recent advances in CAD systems and related techniques, described some fundamental concepts related to breast cancer detection and reviewed many key CAD techniques for breast cancer: including detection of masses, calcification, architectural distortion, bilateral asymmetry in mammograms. Even though important improvement has been made more than the last 20 years, a large amount work still needs to be done to build up more effective CAD systems. Effective and efficient CAD systems should direct to early on detection of breast cancer and better diagnosis for those affected by the disease.

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