Use of Concentric Morphology Model in Detection of Masses from Mammograms: A Review

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ABSTRACT
Breast cancer is one of the most common cancers among women worldwide. Mass detection from mammogram helps in early detection of breast cancer. A Computer Aided Detection (CAD) system which will help to identify and detect the malignant masses in human breast in an accurate and cost effective way is needed. It has been the dream and aim of researchers to have a CAD system with maximum sensitivity and low false positives per image (FPI). Detection of mass from human breast is difficult due to its abundant morphological characteristics and ambiguous margins. Mass detection performance can be improved by using effective preprocessing mechanism and morphological characteristics of the mass regions. As a mass develops, it disturbs the breast parenchyma and spreads by developing multiple concentric layers. Morphological analysis of these concentric layers is a corner stone in mass detection algorithm. Various CAD systems using concentric morphology model exist in the literature. In this paper an attempt has been made to summarize some of the existing CAD systems which use concentric morphology model for early and accurate detection of masses.

General Terms
Biomedical; Automated system.

Keywords
Breast cancer; Mammography; Computer Aided Detection; Mass detection; Concentric morphology model.

1. INTRODUCTION
Breast cancer is the topmost cancer among women both in developing and developed countries. World health organization statistics show that almost 3,60,000 people die a year and almost 9,00,000 new cases are reported every year. If detected at an early stage it is possible to cure breast cancer and death rate can be reduced to a great extent. Mammogram analysis is the most common and cost effective method that is used for detecting masses.

Mammography is the process of using low dense amplitude X-Rays to examine human breast and is used as a diagnostic tool. Radiologist analyses the mammogram and detects masses. In earlier days two radiologists used to cross check the mammograms to reduce errors in detection. Even though double reading was done human errors were quite normal and it is costly. In order to overcome it Computer Aided Detection (CAD) and Computer Aided Diagnosis (CADx) system was introduced. CAD helped to identify the masses and classification of masses into benign and malignant masses was done by CADx system. CAD system was developed as an aid to the radiologist and it assists the radiologist in identification of potential abnormalities and reduces the number of missed lesions. Now CAD and CADx systems are considered as a complete system which will identify and classify masses. It is implemented for early and accurate detection of breast cancer but till date there is not even a single CAD and CADx system with no false positives and false negatives. So lots of researches are going on in this area to have a fault free system.

Mass detection from mammograms plays an important role in breast cancer detection. Accurate detection of mass makes it possible to detect breast cancer at an early stage and it also avoids a patient without cancer undergoing unnecessary clinical formalities. Mass detection is done by analyzing two views of a human breast: the craniocaudal (CC) view, which is the top to bottom view, and the mediolateral oblique (MLO) view which is a side view taken at an angle. Examples of CC view and MLO view are shown in Figure 1.1 [Sampat et al. 2005].

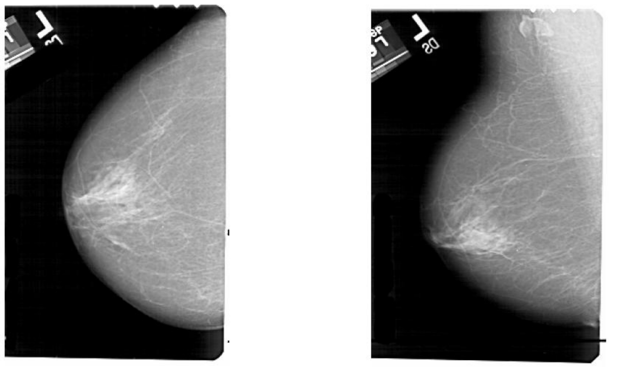

Fig 1: Two views of breast: the craniocaudal (CC) view, mediolateral oblique (MLO) view.

There are two major areas in a mammogram, breast region and non-breast region. The breast region contains pectoral muscle, breast tissues or mass and the non-breast region contains dark background and background objects. Some of the important signs of breast cancer that radiologists look for are clusters of microcalcifications, masses, and architectural distortions. A mass can be defined as a space occupying lesion seen in different projections [Senthil Kumar et al. 2011]. Masses are described by their shape and margin characteristics. Calcifications are tiny deposits of calcium, which appear as small bright spots on the mammogram. They are characterized by their type and distribution properties. Architectural distortions are the effects produced by the addition of noise and unwanted particles in the mammogram while the scanning is done. Detection of masses are more difficult than other cancer symptoms because their features can be more obscured or similar to normal breast parenchyma [Senthil Kumal et al. 2011].

The aim of this paper is to provide an overview of the mass detection algorithms and some of the existing CAD systems. It is also intended to draw the attention of more research scientists to the importance of Multiple Concentric Layer criteria in mass detection algorithms.

The rest of the paper is organized as follows. In Section 2, the general structure of mass detection algorithms are described. Each stage in CAD systems and the metrics used for measuring the performance of mass detection algorithms are also discussed. In Section 3, some of the existing CAD systems are reviewed. Importance of mass specific characteristic like Multiple Concentric Layer criteria is also described here. Section 4 concludes the paper.

2. MASS DETECTION ALGORITHM

Computer Aided Detection (CAD) system assists the radiologist in locating masses on the mammograms. A lot of researchers are working on the detection of masses in mammograms. Masses occur in different shape and size. Spiculated masses have high likelihood of malignancy. A spiculated mass is characterized by lines radiating from the margins of the mass. Since all the malignant masses are not spiculated, detection of non spiculated masses are also important. The main steps involved in the detection (CAD) and diagnosis (CADx) of mammographic abnormalities is shown in figure 1.2 [Sampat et al. 2005].

Generally any mass detection algorithm has two stages. In stage one; the aim is to detect suspicious lesions at a high sensitivity. This stage is known as detection stage. In stage two, the aim is to reduce the number of false positives without decreasing the sensitivity drastically. Classification of the suspicious region into mass or normal tissue is done in stage two. So this stage is called classification stage. Each of these stages contains preprocessing, feature extraction, feature selection and classification steps. In some approaches some of the steps may involve very simple methods or be skipped entirely.

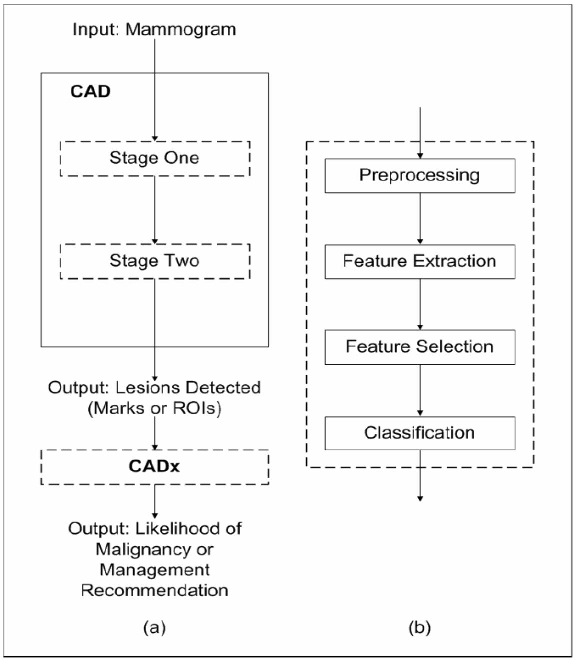

Fig 1.2: Steps in detection (CAD) and diagnosis (CADx) of mammographic abnormalities.

Preprocessing step consists of noise removal, enhancement and segmentation phases. Noise removal and enhancement are used for improving the image quality. The aim of the segmentation step in mammographic image analysis is to extract regions of interest (ROIs) containing all breast abnormalities from the normal breast tissue. Another aim of the segmentation is to locate the suspicious lesion candidates from the region of interest. In the feature extraction step of the mass detection algorithm the features are calculated from the characteristics of the region of interest. Some of the features extracted from the regions of interest in the mammographic image are not significant when observed alone, but in combination with other features they can be significant for classification. The best set of features for eliminating false positives and for classifying lesion types as benign or malignant are selected in the feature selection step. In the classification step the suspicious regions are classified as mass or normal tissue on the basis of selected features. The detection system (CAD) output is the masses. These masses or regions of interest (ROI) are given as input to the diagnosis system (CADx).

Algorithms used in detection stage of mass detection algorithm are either pixel based or region based. In the pixel based approaches, features are extracted for each pixel and classified as normal or suspicious. In the region based approach, ROIs are segmented, and then, features are extracted from each region, which are subsequently used to classify the region as suspicious or not suspicious [Jinshan Tang et al. 2009].

Sensitivity and False Positives per Image (FPI) are the matrices used for reporting the performance of mass detection algorithms. Sensitivity is the total number of true positive marks among the total number of lesions and false positives per image (FPI) is the number of false positive marks among total number of images. A true positive mark is a mark made by the CAD system that corresponds to the location of a lesion. A false positive mark is a mark made by the CAD system that does not correspond to the location of a lesion. A plot of sensitivity versus FPI is called a Free-Response Receiver Operating Characteristic (FROC) plot and this is generally used to report the performance of the detection algorithm. An efficient CAD system will have maximum sensitivity and minimum FPI.

Digital Database for Screening Mammography (DDSM) and Mammographic Image Analyses Society (MIAS) database are the most commonly used databases of Mammogram images by researchers for the purpose of analysis, detection and diagnosis of breast cancer.

Any mass detection algorithm should be able to identify all masses in a mammogram without falsely selecting a normal tissue as mass. But the main tradeoff between sensitivity and FPI is that an attempt to reduce FPI may reduce sensitivity. So at most care has to be taken while attempting to reduce FPI. FPI reduction has to be achieved without reducing sensitivity. None of the existing system has achieved 100% detection accuracy.

Many commercial CAD systems are available. Even though they have achieved maximum accuracy in detecting microcalcifications, mass detection accuracy has to be improved. Two of the commercial computer aided detection and diagnosis systems are: R2 Technology Image Checker with a reported mass detection performance of 85.7% with 1.42 FPI and Intelligent System Software, Inc. (ISSI) with a reported mass detection performance of 87.4% with 3.32 FPI

[Sampat et al. 2005]. Maximum accuracy can be obtained by selecting suitable algorithms for each of the stages of mass detection algorithm. Most of the existing algorithms have mass detection accuracy of 90% at 1-10 FPI. So there is still room for improving the detection rate of masses in CAD.

3. COMPUTER AIDED DETECTION OF MASSES FROM MAMMOGRAMS

There is extensive literature on the development and evaluation of CAD systems in mammography. A number of schemes have been developed for mammographic mass detection. Different approaches have been used in these schemes. All of these methods used different combination of image processing techniques for implementing the two stages of mass detection algorithm. None of these techniques have succeeded in achieving a 100% accuracy. Majority of these techniques were focusing on the image features of the mammogram rather than considering characteristics of masses in mammogram and these techniques were not so successful in achieving maximum detection rate.

Early detection schemes used simple enhancing or filtering techniques. Later some complex techniques were developed. Brake and Karssmeijer[Brake and Karssmeijer. 1999] proposed mass detection scheme using single and multiscale styles; Mudigonda et al. [Mudigonda et al. 2001] investigated the use of a density slicing method to segment the region of interests (ROIs). These methods have sensitivities around 90% with 1-10 false positives per image (FPI). Some of the recent studies considered essential characteristics of masses for detection. Timp and Karssmeijer [Timp and Karssemeijer 2006] analyzed the interval changes between two mammographic images in feature space. They were successful in finding small lesions and architectural distortions.

3.1 Use of MCL Criteria in Mass Detection

Development of a mass disturbs the breast parenchyma and spreads by developing concentric layers. Masses possess a highlighted focal region with some successive dimmer concentric layers. So gradient and morphological features are most frequently used for mass recognition. Taking this into consideration Eltonsy et al. [Eltonsy et al. 2004] investigated the morphological characterization of the layers of mass for developing an automated scheme for detection of masses. This method focuses on the detection stage of mass detection algorithm by prescreening mammogram to select suspicious breast regions that may contain malignant masses. These regions are the candidates for the second stage (classification) of the CAD system.

In this study initially after granulating the breast region into 50 regions with different intensity ranges, a connectivity rule is applied to create a new image with reduced number of granules. Then these granulated regions are analyzed using the processing module to identify the number of concentric layers. Finally, concentric group with the highest number of concentric layers, and with considerable level of spiculation are picked as the final suspicious regions. Spiculation constraint is added because it is clinically established that malignant masses tend to form spiculations [Eltonsy et al. 2004].

This method was tested using mammograms from Digital Database for Screening Mammography (DDSM). Craniocaudal views of the mammograms were used in this study. This method when implemented using 42 biopsy proven masses in total (21 malignant masses and the remaining 21 benign masses) reported 85.7% sensitivity with an average of 0.53 false positives per image [Eltonsy et al. 2004]. After more extensive evaluation of the system on a larger set of mammograms, the observed performance was 92% sensitivity with 3.26 FPI [Tourassi et al. 2005].

Tourassi et al. [Tourassi et al. 2005] did an extension of the work done by Eltonsy et al.[Eltonsy et al. 2004]. They proposed a false positive reduction strategy using an artificial neural network that merges feature and knowledge based analysis of suspicious mammographic locations. This scheme will act as the second phase of the CAD system (classification). The system performs the following steps: 1) Preprocessing and segmentation of suspicious regions. 2) Feature based and knowledge based analysis of suspicious regions and 3) Classification for false positive reduction.

The preprocessing module used the scheme developed by Eltonsy et al. [Eltonsy et al. 2004] to identify and segment the suspicious regions. Feature analysis investigates both the directional and textural characteristics of the suspicious regions. Feature analysis module captures one of the most common representations of malignant masses. Parallel to feature analysis a knowledge based module is used for refining the false positive reduction process. This module uses a reference library where mammographic cases with known truth are stored and mutual information is used as the similarity criterion between a query case and archived case. Knowledge based analysis produces a decision index that measures the relative similarity between the query case and the archived case. The features from feature analysis phase and the decision index from knowledge based analysis phase are merged into a final decision using a back propagation artificial neural network. This study used mammograms from Digital Database for Screening Mammography (DDSM). This scheme is reported to have achieved 87.4% sensitivity with 1.8 false positives per image [Tourassi et al. 2005].

Eltonsy et al.[Eltonsy et al. 2007], proposed a multiple concentric layers (MCL) based algorithm to detect masses in mammograms. The proposed detection scheme is a rule based algorithm that relies on a morphological model of breast cancer growth. Morphological analysis of the concentric layer model is the corner stone of MCL detection algorithm. The algorithm consists of three steps: First, the breast regions are preprocessed by segmentation and granulation techniques. Then, the suspicious focal areas are detected using knowledge based reasoning. Finally, two different criteria are applied to eliminate false positives. In the detection stage after localizing the focal areas with the suspicious morphology, minimum distance criterion is used to perform initial elimination of suspicious regions. Then Multiple Concentric Layer criteria are applied for selecting masses. False positive reduction is achieved through the analysis of relative incidence and minimum distance criterion.

They used mammogram images from Digital Database for Screening Mammography (DDSM) database for their experiments. They chose 270 CC views of mammographic cases with biopsy proven malignant masses. One half of the cases were used for training and the other half for testing. The performance reported by the authors is 92% sensitivity for malignant masses at 5.4 FPI [Eltonsy et al. 2007].

Xinbo Gao et al. [Xinbo Gao et al. 2010], introduced a new method which combines concentric morphology model(MCL) with morphological component analysis(MCA). This method overcomes the drawbacks in MCL criteria. Use of MCA for preprocessing has increased the detection accuracy. In this method MCA is used to decompose the image into piecewise smooth component and texture component. Further processing is done on piecewise smooth component. Then masses are detected using concentric layer criteria. Major stages in this algorithm are: preprocessing, morphological feature extraction and rule based detection.

In this method mammogram images are preprocessed using MCA. MCA is a decomposition method based on sparse representation of data. This method relies on the assumption that each signal is a linear mixture of several atomic signals of more coherent origin. For every atomic signal behavior to be separated there exists a dictionary that enables its construction using a sparse representation. Also, it is assumed that the different dictionaries are highly inefficient in representing the other behaviors in the mixture. This dictionary along with a suitable Pursuit algorithm searching for the sparsest representation leads to the desired separation. Over complete dictionaries are used in this method. Undecimated Wavelet Transforms and Local DCT are the proper choice of transforms for dictionary representations since it effectively separates texture component and piecewise smooth component. Piecewise smooth components are then separated into different intensity layers using multiple intensity thresholds. All the regions in these independent layers are used for further processing. Then morphological features are extracted from these layers to select the suspicious areas. Morphological features used in this method include solidity, eccentricity, extent and contrast. Rule based detection stage is used for further removal of unnecessary regions. For reducing false positives minimum distance criterion and analysis of relative incidence are used [Xinbo Gao et al. 2010].

This scheme was tested using 100 benign and 50 malignant cases from the Digital Database for Screening Mammography (DDSM) database. The reported sensitivity of this scheme is 99% in malignant, 88% in benign and 95.3% in all types of cases with 2.7, 3.1 and 2.83 FPI respectively [Xinbo Gao et al. 2010].

A summary of the performance of methods described in this literature survey is given in the Table 1. It is not possible to make a comparison between these different algorithms since they have not been trained and tested on the same datasets. It can be seen from the table that the use of different datasets with the same algorithm produces different results.

Table 1. A summary of mass detection algorithms using MCL criteria.

Author	No. of Images	Sensitivity	FPI
Eltonsy et al., 2004	42	85.7%	0.53
Eltonsy et al., 2004	150	92%	3.26
Tourassi et al., 2005	150	87.4%	1.8
Eltonsy et al., 2007	270	92.1%	5.4
Xinbo Gao et al., 2010	150	95.3%	2.83

A CAD system will have maximum performance if the sensitivity of the system is maximum and FPI is minimum. CAD system determines the detection accuracy of breast cancer detection. So the need for a CAD system with maximum sensitivity and minimum or no FPI is high. Introduction of MCL criteria in mass detection scheme have improved the accuracy of mass detection. Among the existing systems detection scheme using Morphological Component Analysis and Concentric layer model have maximum sensitivity with compromising FPI. It has to be noted that this scheme have achieved 99% sensitivity for malignant masses with 2.7 FPI. So reduction in FPI will improve the accuracy.

4. CONCLUSION AND FUTURE WORK

Early detection of breast cancer is very important to reduce the mortality rate. In order to make it possible, an automated detection system is needed. Many mass detection schemes have been developed but a CAD system with 100% accuracy still remains as a researcher's dream. In this paper an attempt is made to identify a mass detection scheme which has high sensitivity and low false positive rate. From the literature survey it is found that most of the current CAD systems have sensitivity around 90% with 1-10 false positives per image. Introduction of MCL criteria has improved the accuracy of mass detection algorithms. The mass detection scheme using a combination of morphological component analysis (MCA) and multiple concentric layer criteria (MCL) have maximum sensitivity (99% with malignant masses with 2.7 FPI). So this mass detection algorithm has great future enhancement prospects.

Reduction of false positives will improve the performance to a great extent. The use of mass region specific characteristics has a great role in identification and detection of masses. Identification of proper feature will help to reduce the false positives. It is expected that addition of new features such as Gaussian distribution characteristics of mass regions will reduce false positives since intensity distribution of mass region are similar to 2-D projection of Gaussian surface. Use of better dictionaries for MCA will further improve the detection results.

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