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Early Breast Cancer Detection using Mammogram Images: A Review of Image Processing Techniques

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Breast cancer is one of the most common cancers worldwide among women so that one in eight women is affected by this disease during their lifetime. Mammography is the most effective imaging modality for early detection of breast cancer in early stages. Because of poor contrast and low visibility in the mammographic images, early detection of breast cancer is a significant step to efficient treatment of the disease. Different computer-aided detection algorithms have been developed to help radiologists provide an accurate diagnosis. This paper reviews the most common image processing approaches developed for detection of masses and calcifications. The main focus of this review is on image segmentation methods and the variables used for early breast cancer detection. Texture analysis is the crucial step in any image segmentation techniques which are based on a local spatial variation of intensity or color. Therefore, various methods of texture analysis for mass and micro-calcification detection in mammography are discussed in details.

Key words: Breast Cancer, Early Detection, Image Processing, Image Segmentation, Texture Analysis.

Among the leading causes of cancer affecting females, breast cancer is ranked first and 1 out of 10 women in their lifetime are affected by this disease. In order to early detection of masses and abnormalities for breast cancer, mammogram is the most important technique that can detect 85 to 90 percent of all breast cancers. Breast lesions can indicate benign or malignant changes and sometimes indistinguishable from the surrounding tissue which makes the detection and diagnose of breast cancer more difficult. Reading mammograms is a very demanding job for radiologists. Radiologist's misinterpretation of the lesion can lead to a greater number of false positive cases. Computer aided detection (CAD) techniques by processing and analyzing mammogram images can help to radiologist for mass detection and classification. The detection sensitivity without CAD is 80% and with CAD up to 90%[1]. Most image processing algorithms include steps such as Preprocessing, Segmentation, Feature extraction, Feature selection and Classification. Preprocessing is the first step in image processing. In order to reduce the noise and improve the quality of the image, it has to be done on digitized images. To find suspicious regions of interest (ROIs) containing abnormalities, the segmentation step is applied. The most studied version of grouping in computer vision is image segmentation. Image segmentation is one of the most important tasks in automatic image processing[2]. In general, image segmentation is process of dividing an image into homogenous groups such that each region is homogenous but the union of no two adjacent regions is homogenous[3]. Image segmentation techniques can be classified into two broad

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categories (a) region-based, and (b) contour-based approaches. Image segmentation plays a crucial role in many medical imaging applications by automating or facilitating the delineation of anatomical structures and other regions of interest. In the feature extraction step the features are calculated from the characteristics of the region of interest. In feature selection the best set of features are selected for eliminating false positives and for classifying lesion types. Feature selection is a selecting a smaller feature subset that leads to the largest value of some classifier performance function[4]. Finally, on the basis of selected features the false positive reduction and lesion classification are performed in the classification step.

In computer vision and image processing for classification and segmentation of image based on a local spatial variation of intensity or color, texture analysis is widely used[5-6]. Existing texture analysis can be classified into statistical and structural methods. Statistical approach computes different properties and is suitable if texture primitive sizes are comparable with the pixel sizes. In structural texture analysis method, the texture region is defined to have a constant texture if a set of local statistics or other local properties of the image are constant, slowly varying or approximately periodic[7].

Historical Review of CAD Development

Limitations in the human eye-brain visual system, reader fatigue, distraction, and the vast number of normal cases seen in screening programs cause that radiologists do not always correctly characterize abnormalities in the medical images. A CAD tool can help to improve diagnostic accuracy of radiologists, lighten the burden of increasing workload. Two typical examples of application of CAD in clinical areas are the use of computerized systems in mammography and chest CT and radiography.

During the mid-1950s, Lusted discussed the use of computers in the analysis of radiographic abnormalities[8]. In the 1960s and 1970s, researchers started to investigate analyses on breast images and chest radiographs. In 1963, Lodwick *et al*.,[9] investigated the use of a computer in diagnosing bone tumor. In 1964, Meyers *et al*. proposed a system automatically distinguish normal chest radiographs from abnormal chest radiographs[10]. In 1967, Winsberg *et al*.,[11] described their study on computer analysis and detection of radiographic abnormalities in mammograms. Ackerman and Gose[12] in 1972 proposed another early computer system for breast cancer detection. In the 1980s, however, another approach emerged which assumed that the computer output could be utilized by radiologists, but not replace them. This concept is currently known as computer-aided diagnosis, which has spread widely and quickly.

The year 1998 is one of the most important years in the history of CAD. It marked the transition of CAD technologies from the research phase to industrial practice with the success of the ImageCheckerTM in obtaining a Food and Drug Administration (FDA) approval.

Today, three commercially available CAD systems have been approved for clinical use by the Food and Drug Administration: ImageChecker, Second Look (CADx Medical Systems, Laval, Quebec, Canada), and MammoReader (Intelligent Systems Software, Clearwater, Fla).

Typical steps in image processing algorithms

The Proposed Method of Detection for Masses in Digital Mammogram are image preprocessing, image segmentation, feature extraction and selection, classification and evaluation[13].

Image preprocessing

The general methods for image preprocessing are divided into three branches such as denoising, enhancement of structure and enhancement of contrast. Current enhancement techniques for mammograms are un-sharp masking[14] region-based enhancement[15] Adaptive neighborhood contrast enhancement (ANCE)[16] optimal adaptive enhancement[17] and dyadic and Hexagonal wavelet transform[18].

Image Segmentation Techniques

Partitioning an image into regions such that each region is homogeneous with respect to one or more properties (such as brightness, color, texture, reflectivity, etc.) is image segmentation[3,19,20]. Common image segmentation methods are thresholding, edge based segmentation, region based segmentation, clustering, classifier based segmentation and deformable model based segmentation.

Edge Detection Based Segmentation

In a digital image if there is a difference in intensities or abrupt change in image brightness, then Edge detection refers to algorithms which try to identify points. These points are then linked together to form closed object boundaries and produce a binary image[21].

Two main edge based segmentation methods are gray histogram and gradient based method[22]. Edge detectors have different operator for detection of edge such as Sobel operator, Laplace operator, canny operator, Log (Laplacian of Gaussian) operator and so on.

Thresholding Techniques

Thresholding is an old, simple and popular technique for image segmentation[23]. Weszka provided a survey of threshold selection methods[24] and Sahoo provided an overview of thresholding techniques[25].

Global thresholding[26] is one of the common techniques for image segmentation. It is based on the global information such as histogram. The fact that masses usually have greater intensity than the surrounding tissue can be used for finding global threshold value. On the histogram, the regions with an abnormality impose extra peaks while a healthy region has only a single peak[1].

In local thresholding, a threshold value is defined locally for each pixel based on the intensity values of its neighbor pixels. Multiple pixels belonging to the same class (pixels at the periphery of the mass and pixels at the center of the mass) are not always homogenous and may be represented by different feature values. Li *et al.*,[27] used local adaptive thresholding to segment mammographic image into parts belonging to same classes and an adaptive clustering to refine the results.

Li *et al.*,[28] used adaptive gray-level thresholding to obtain an initial segmentation of suspicious regions followed by a multiresolution Markov random field model-based method.

In thresholding method two artifacts corrupt the histogram of the image, making separation more difficult. Firstly in this method only two classes are generated and it cannot be applied to multichannel images. secondly thresholding is sensitive to noise because it does not take into account the spatial characteristics of an image[22].

Region Based Segmentation Methods

Regions within an image are a group of connected pixels with similar properties. In the region approach image processing, each pixel is assigned to a particular object or region. In other word region based methods partition an image into regions that are similar according to a set of predefined criteria[29].

Region growing, split and merge, and watershed methods are three basic region based segmentation techniques.

a) Region growing group pixels in an entire image into sub regions or large regions based on predefined criterion. In other words, the basic idea is to group a collection of pixels with similar properties to form a region. This process is iterated for each boundary pixel in the region. When adjacent regions are found, a region-merging algorithm is used through which weak edges are dissolved and strong edges are left intact. The algorithm is also very stable to noise. However, the main limitation is that it needs a seed point which indicates a manual interaction. Thus, each region to be segmented, a seed point is needed.

b) Region Splitting and Merging: In this technique, the image is subdivided into a set of arbitrary unconnected regions and merge/split the region according to the condition of the segmentation. This particular splitting technique is usually implemented with theory based on quad tree data. Quad tree is a tree in which each node has exactly four branches (30) This include following steps:

a) Start splitting the region into four branches.

b) Merge any region when no further splitting is possible. Stop when no further merging is possible.

Clustering

The process of classifying observations (data items, patterns, or feature vectors) into groups is clustering (called clusters)[31]. In other word, clustering is a process of organizing the objects into different groups based on their attributes. An image can be grouped based on keyword or its contents. The similar features of an image is describes by keyword, whereas content refers to shape, texture etc. Both supervised and unsupervised clustering techniques are used in image segmentation. The main clustering algorithms are hard clustering, k- means clustering, fuzzy clustering, etc.

Segmentation based on artificial neural network

Neural network segmentation method includes two important steps: feature extraction and image segmentation based on neural network. Neural network is an artificial representation of human brain constitutes a large number of parallel nodes for simulation of life, especially the human brain's learning process. Each node can perform some basic computing. The learning process can be achieved through the transferring the connections among connection weights and nodes[32].

Watershed/fast region merging Hybrid segmentation[33]

The main segmentation problem is how to segment an image into homogeneous segments such that it results in a heterogeneous segment following the combination of two neighbors. Several techniques have been proposed for an error-free image partitions as histogram-based represents the simple probability distribution function of intensity values of any image. Edge based technique is used to detect using differential filter in order of image gradient or Laplacian and then grouped them into contours representing the surface[33].

In the region-based segmentation technique the image is segmented into a set of homogeneous regions, then they are merged according to certain decision rules[34]. In the Markov random field based segmentation technique the true image is realized by a Markov or Gibbs random field with a distribution function. Hybrid segmentation techniques are combined such as edge based and region based techniques. In this image is firstly partitioned into regions and then merged them using split and merge technique and after that detected the contours using edge-based technique.

Color Image Segmentation[35]

Three phases in the color images segmentation are preprocessing, transformation and segmentation. In the preprocessing, morphological methods are applied to eliminate noises from images through smoothing some spots on uniformed patterns. In transformation, color space transformed methods are used to transform other color space to Red-Green-Blue (RGB) space[35]. The average intra-cluster distance based method is a traditional method applied for transformation. In Segmentation, clustering algorithm like K-means algorithm is applied for finding the appropriate cluster numbers and segment images in different color spaces. The cluster with the maximum average variance is split into new clusters.

Model Based Segmentation

The human eyes are capable of recognizing objects even if they are not completely visible. All the algorithms mentioned above utilize only local information. In this case, we require specific knowledge about the geometrical shape of the object, which can then be compared with the local information to recreate the object. This segmentation technique is applicable only if we know the exact shape of the objects contained in the image.

Feature extraction

Feature extraction is a very important process for the overall system performance in the classification of micro-calcifications. The features extracted are distinguished according to the method of extraction and the image characteristics. Thus, the following categorization of the features can be applied:

a) Features extracted directly from mammogram, such as perimeter, area, compactness, elongation, eccentricity, thickness, orientation, direction, line, background, foreground, distance and contrast. They are easy to extract and they originate from the experience of radiologists;
b) Features extracted from spatial grey level dependence matrix (co-occurrence matrix);
c) Features extracted from the grey-level run-length (GLRL) matrix;
d) Features extracted from the grey-level difference (GLD) matrix;
e) Energy, entropy and norm extracted from the wavelet transform sub-images;
f) Features extracted from the fractal model of an image;
g) Features used to describe the distribution of the micro-calcification, cluster area and number of micro-calcifications in an area. In the following sections we summarize these different methods of feature extraction.

Shape Feature Extraction

Shape feature extraction is a low-level image representations for CAD tasks such as template matching, image collaboration and object recognition extracted from mammogram have been used by several research groups to directly describe individual micro-calcification (Soltanian-Zadeh *et al.,*[36] Veldkamp *et al.*,[37]). Shape feature extraction techniques can be classified into two groups [Zhang, 2004 #151]: Contour based and region based methods. The contour based technique calculates shape features only from the boundary of the shape, while the region based method extracts features from the entire region.

Methods for extracting features are segmentation of micro-calcifications, labeling of micro-calcifications and extracting shape features.

Statistical Feature Extraction

Kim and Park[38] comparatively investigated the performances of the surrounding region dependence method (SRDM) and other conventional statistical texture-analysis methods for detecting clustered micro-calcifications in digitized mammograms such as spatial gray level dependence matrix (SGLDM)[4], grey level run-length method (GLRLM), gray level difference method (GLDM)[38], gray level histogram moments (GLHM)[39], gray level co-occurrence matrix (GLCM).

Multiscale Texture Features Extraction-Wavelet Based Method

Wavelet theory offers multiresolution analysis which is a powerful framework for feature extraction techniques. Using the multiresolution capability, the wavelet transform could separate small objects such as micro-calcifications from large objects such as large background structures. Micro-calcifications are relatively high-frequency components buried in the background of low-frequency components and very high-frequency noise in the mammograms. Wavelet analysis is appropriate tool for extracting micro-calcifications from low-frequency backgrounds and high-frequency noise contents. In particular, the wavelet transform separates a signal into signal bands of different frequency ranges. This method obtains micro-calcifications related information and discards the signal bands with little contribution into detection.

Multi-Wavelet Features

Multi-wavelet transform can be used to generate a useful multi-scale representation. Unlike a scalar wavelet, a multi-wavelet uses several scaling functions and mother wavelets[40-41].

Cluster features extraction. Following detection of individual micro-calcifications cluster features are used to group them into corresponding clusters.

Classifiers

Classifiers play an important role in the implementation of computer-aided diagnosis of mammography.

Some kinds of classifiers are given below.

Neural networks

The artificial neural networks (ANNs) are non-parametric pattern recognition systems that can extract general rules by learning from real data or examples. Where decision rules are vague and there is no explicit knowledge about the probability density functions governing sample distributions, this method is useful. The key characteristics of the artificial neural networks are the distributed representation, the local operations and nonlinear processing.

K-nearest neighbor classifiers

K-nearest neighbor (KNN) classifier distinguishes unknown patterns based on the similarity to known samples. The KNN algorithm computes the distances from an unknown pattern to every sample and selects the K-nearest samples as the base for classification. The unknown pattern is assigned to the class containing the most samples among the K-nearest samples.

Binary decision tree

This technique makes a tree to classify a set of input examples according to their class and each branch in the tree represents a decision and each node in the tree refers to a particular attribute. Edges connecting nodes are labeled with attribute values and leaf nodes give a classification that applies to the examples that were reached through that branch. At each step of the tree construction a node is selected according to a statistical measure called information gain that measures how well a node (attribute) distributes the input examples against their class. Kuo *et al.,*[42] used data mining approach with a decision tree model to classify breast tumors.

Support vector machines

They are learning machines used in pattern recognition and regression estimation problems. They grow up from statistical learning theory (SLT) problems, which give some useful bounds on the generalization capacity of machines for learning tasks. The SVM algorithm constructs a separating hyper surface in the input space.

Some another feature extraction techniques are include: texture features[43], radial edge gradient analysis[44], gray-level image structure features[45] morphological-based features[46] and Fuzzy-neural modeling[47].

Features Selection

Feature selection (FS) is an important part of any machine learning task. The success of a classification scheme mainly depends on the selected features and the values of associated information they provide in the model. Last decade has witnessed various feature selection approaches including artificial neural network, deterministic single solution that is divided into stepwise linear discriminant analysis and sequential forward selection methods, deterministic multiple solution methods, stochastic single solution methods involve simulated annealing and stochastic multiple solution methods involve genetic algorithms.

Another category of FS methods have been developed based on the analyzing data of hundreds or thousands of variables. These methods are grouped into filters, wrappers, and embedded methods. More recently, a new group of methods has been added in the general framework of FS: ensemble techniques.

Filter model algorithms rely on analyzing the general characteristics of data and evaluating features without involving any learning algorithm. Feature selection algorithms of wrapper model require a predetermined learning algorithm and use its performance on the provided features in the evaluation step to identify relevant feature. Algorithms of the embedded model, e.g., C4.5 [49], least angle regression (LARS)[50], 1-norm support vector machine[51], and sparse logistic regression[52], incorporate feature selection as a part of the model fitting/training process, and features' utility is obtained based on analyzing their utility for optimizing the objective function of the learning model. Algorithms of the filter model are independent of any learning model, therefore do not have bias associated with any learning models and on the other hand allows the algorithms to have very simple structure, which usually employs a straightforward search strategy, such as backward elimination or forward selection, and a feature evaluation criterion designed according to certain criterion.

Ensemble feature selection[53-54] is a relatively new technique used to obtain a stable feature subset.

Examples for filter models are i-test, gain ratio[55], Correlation-based feature selection (CFS)[56], Markov blanket filter (MBF)[57] and fast correlation-based feature selection (FCBF)[58]. For wrapper models, the examples are Sequential forward selection (SFS)[59],Sequential backward elimination (SBE)[59], beam search[60], simulated annealing randomized hill climbing[61], genetic algorithms[62], Estimation of distribution algorithms[63] and finally for embedded model the examples are decision trees weighted naive/bayes, feature selection using the weight vector of SVM[64-65].

CONCLUSION

Breast cancer is one of the major causes of death among women. Due to the wide range of features associated to breast abnormalities some abnormalities may be missed or misinterpreted. There is also a number of false positive findings and therefore a lot of unnecessary biopsies. Computer-aided detection and diagnosis algorithms have been developed to help radiologists give an accurate diagnosis and to reduce the number of false positives.

In this study typical steps in image processing algorithms have been extensively studied. The techniques in the field of computer aided mammography include image preprocessing, image segmentation techniques, feature extraction, feature selection, classification techniques and features for mammograms. Further developments in each algorithm step are required to improve the overall performance of computer aided detection and diagnosis algorithms. In image segmentation study, the overview of various segmentation methodologies applied for digital image processing is briefly explained.

Texture analysis is a method to classify benign and malignant masses and to identify the micro-calcification in mammography. Finally, various texture analysis approaches for the detection of masses and micro-calcification in mammography have been discussed.

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