SEGMENTATION METHODS FOR LOCATING MASSES AND LOCATING BREAST BOUNDARIES: A SURVEY

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Abstract: *The mammography is the most effective procedure for an early diagnosis of the breast cancer. The goal of segmentation is to detect abnormalities and to extract the entire suspicious mass region from mammograms. In this paper we have reviewed different segmentation methods of mammograms for the detection of breast cancer. Different segmentation methods are studied and their merits and drawbacks are outlined.*

Keywords: *clustering, mammogram, segmentation.*

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I. INTRODUCTION

Breast cancer is a malignant tumor arising from breast cells. The malignant tumor can destroy the nearby cells and spread to different part of the body. Breast cancer is one of the most dangerous types of cancer among women all over the world and it can also affect men, although the male breast cancer is rare [1]. The reports of recent studies show that breast cancer affects one of every eight women in the United States and one of every ten in Europe [2]. Therefore, the effective way to reduce the mortality is early detection and treatment of breast cancer.

Mammography is the most commonly used methods for early detection and diagnosis of breast cancer [3]. Mammography is a specific type of imaging that uses a low-dose x-ray system to examine breasts. It is used to find tumors and to identify the difference between benign and malignant cells. Benign is a noncancerous cell and it do not spread to other parts of the body. But malignant is a cancerous cell and that can spread to other parts of the body [4]. It has been found that the interpretation of mammograms by radiologist, many a times give high rates of false positive cases [5]. In the breast cancer analysis the estimated sensitivity of radiologist is only about 75%. So, different effective and efficient diagnostic methods based on image processing algorithm have been developed by the researches. Different segmentation methods have been suggested to improve the accuracy of interpretation.

Most of the cancer detection algorithm will be performed in four different stages [6]. It is shown in fig.1. The first stage is image preprocessing. In this stage the input image is preprocessed to improve the contrast of the image. So that an effective segmentation can be performed on the preprocessed image. Second stage is segmentation. The aim of image segmentation is to extract the ROIs contacting the suspicious masses from the mammogram. In the third stage, features of the segmented region are extracted to verify whether the extracted region contains masses or not. Finally, the classification of masses will be conducted.

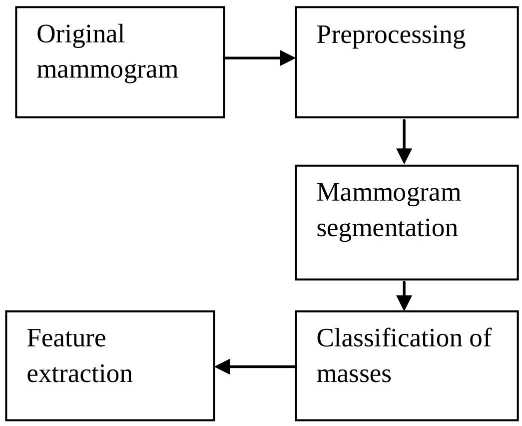

Fig. 1 Stages of cancer detection

Mammogram segmentation techniques are important to classify mammograms into several distinct regions, including the breast border [7], the nipple [8] and the pectoral muscle. Portioning the mammogram into breast and non breast region are the effective way to obtain the breast contours. This paper gives a review of different segmentation methods of mammograms.

II. SEGMENTATION METHODS FOR LOCATING MASSES IN MAMMOGRAMS

The aim segmentation of suspicious areas is to get the location and classify suspicious into benign or malignant. Researchers have used several segmentation techniques and their combinations.

A. Thresholding Segmentation

Thresholding is the simplest method of image segmentation. This is mainly based on a threshold value to turn a gray-scale image into a binary value. If the thresholds depend on the image histogram, it is called as global thresholding. If it is based on local properties such as mean or standard deviation, it is called as local thresholding [9].

Global thresholding is based on histogram of an image. In this the region with abnormalities impose extra peak while a healthy region has only a single peak [10]. This is not an effective way to identify the ROIs because the regions of overlapping tissues of the same intensity levels may be brighter than the masses.

Local thresholding is slightly better for mass detection than global thresholding. It is determined for each pixel by a threshold value and the threshold value is based on the intensity values of the surrounding pixels. The threshold image g (x, y) is defined as:

$$g(x, y) = \begin{cases} 1 \text{ } if \text{ } (x, y) < T \\ 0 \text{ } if \text{ } (x, y) \geq T \end{cases} \quad (1)$$

B. Region Based Segmentation

Region growing is a common segmentation technique. S. Meenalosini, Dr. J. Janet, Dr. E.Kannan showed that the region growing is based on a set of seed pixels [11]. This seed pixel enables the growth of the aggregate pixel which has the similar properties. Pixel classification is also followed on region growing [6]. An adaptive topographic region's growth defines the initial boundary contours. The final mass boundary contour is modified by an active contour algorithm [12]. The region based image segmentation algorithm is shown in fig. 2.

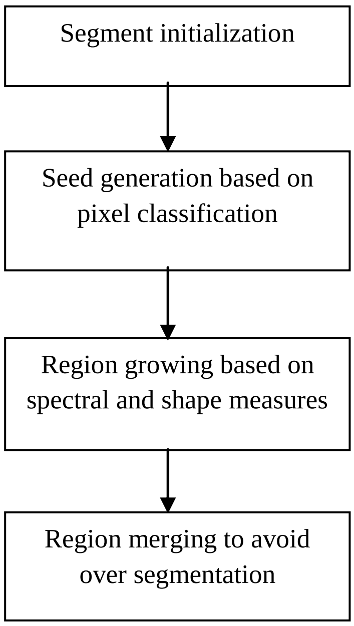

Fig. 2 Overview of the region based image segmentation algorithm

The ROIs according the similarity criterion based on gray level, colour is valued from a searched region based on the reference of seed pixels in region growing technique. In this technique the tissue pattern classification reaches its maximum accuracy. The spatial context of pixels is managed naturally [13]. The effect of computational complexity makes it difficult to use on small regions.

C. Fuzzy C-means Clustering Segmentation

S.S Basha and K.S Prasad used an effective FCM algorithm for the segmentation of breast medical images. The FCM is based on fuzzy set theory. It provides a method that shows how to partition the data points into a specific number of different clusters [14]. Different cluster centers can be determined by the optimization of a cost function [15]. The cost function for FCM is expressed as:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{i\,j}^{m} \left\|x_i - c_j\right\|, \quad 1 \leq \text{m} \infty \quad (2)$$

Where m is a real number greater than one, $u_{i\,j}$ is the member function of the pixel x_i in the cluster j, ||*|| any norm representing the similarity between the cluster center and any measured data. FCM allows pixels to belong to multiple clusters and fuzzy c-means segmentation is more effective for high resolution images. However, there are some disadvantages using FCM segmentation. The performance is mainly depends on initial cluster centers. So it requires a prior knowledge of the number of clusters and cluster centers.

D. K-means Clustering

K-means algorithm is another commonly used method for the segmentation of digital mammogram tumors. K-means algorithm is an iterative technique that partition the data set into K clusters, K can be selected randomly. Each pixel of the image is randomly assigned to the cluster that minimizes the distance between the pixel and the cluster center [16]. If the image pixel is not closest to its own cluster, then that particular pixel will have to be shifted into the closest cluster [17].

K-means clustering is a simple segmentation technique and its computational complexity is very less [18]. This algorithm is inherently iterative; it may not reach the optimal solution.

E. Segmentation Using Markov Fields

H. D. Li, M. Kallergi, et al., used Markov fields for a reliable segmentation of ROIs from the surrounding pixels [19]. Markov fields are a kind of statistical model. This can be used to model spatial constraints, such as smoothness of the image region, spatial regularity of texture in a small region. The posterior probabilities of the segmented image are maximized by this method. The MRFs is used in fine segmentation and thereby improve the preliminary results provided by the coarse segmentation. This function is represented as:

$$Y_{MAP} = \text{arg}\, max_y \;\; P(Y = y\,/X = x) \quad (3)$$

Where X, is the original image and Y, is the segmented image [20]. The problem with Markov field segmentation is that the time of maximization is expensive.

III. SEGMENTATION OF MAMMOGRAM IMAGES TO FIND THE BREAST BOUNDARIES

A. Artificial Neural Network

Karem Daiane Marcomini and Homero Schiabel proposed a new approach for the segmentation of mammograms. An artificial neural network is a computational tool modeled on the interconnection of neurons to resemble the working of human brain [21]. An unsupervised self organization map is mainly used for segmentation, because it does not have a fixed topology. So it can be modified based on the problem.

The neurons in each layer are connected by a link and each link has its own weight associated with it. A learning algorithm is used to adjust the weights by parameterizing the input and the output functions.

Self organization neural networks can separate the breast image into different components such as background, pectoral muscle, glandular tissue and adipose tissue [22]. The difference between background and pectoral muscles can be easily identified by this method. But the background segmentation results are not evaluated properly. A self organization neural network is shown in fig. 3.

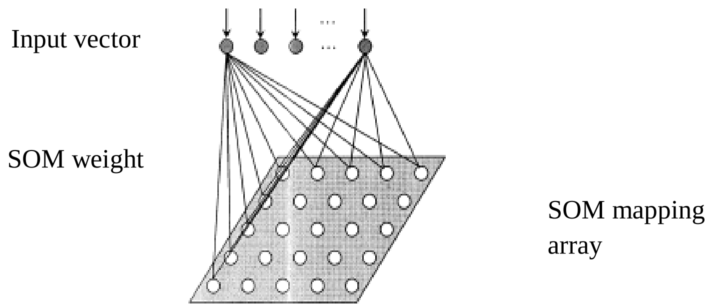

Fig. 3 Structural graph of SOM neural network

B. Watershed Segmentation

Watershed transform is the method of choice for image segmentation in the field of mathematical morphology. This algorithm segments region of an image or volume into catchment basins. The basins are referred to as segments or regions. These segments or regions can share boundary with each other. This can be applied to a topographic surface of an ultrasonic image [23]. Suppose there are holes in each regional minimum, the topography is then flooded and the flooding liquid rises through the holes. Generally Dams are built to prevent the merging of the liquid that arises through the holes. These dams are similar to a line that separates the watersheds [24]. Watershed segmentation is shown in Fig: 4.

This method is simple; even if the image contrast is poor it can produce a complete division of the image in separate regions. However, there are some problems, the watershed may over segment the ultrasonic image and that will give incorrect segmentation results [23].

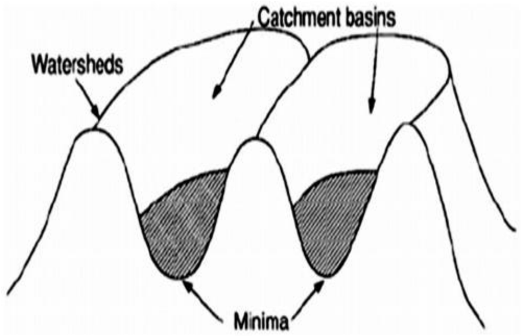

Fig: 4. Watershed segmentation

C. Edge Detection

The boundary between two regions is called as an edge. The edge detection algorithm is based on the gray level discontinuities in the image. Operators like Robert, Sobel, Prewitt, and Laplacian of Gaussian are used for edge detection [25]. In this Sobel operator gives more sharp and clear edges as compared to other operators.

The rate of change of gray level is measured through gradient (or) derivatives [26]. The edge detection is used as the base of other segmentation techniques. Several combined edge detection methods have been developed by the researchers to increase the accuracy.

IV. COMPARISON OF METHODS

The mammogram segmentation techniques are important to separate suspicious areas of masses or micro-calcification from the background texture. Thresholding is a simple method of image segmentation. This can be done by two methods such as global thresholding and local thresholding. Region based segmentation is completely based on initial seed pixels. A clustering based segmentation can be done by fuzzy C-means and K-means clustering algorithm.

Segmentation methods can also be applied to find the breast boundaries. Artificial neural networks, watershed segmentation and edge detection are used to detect the breast boundaries. The watershed segmentation method is simple and fast. In edge detection algorithm the computational time is more. The comparison results of different segmentation methods are shown in Table 1.

TABLE 1

COMPARISON OF MAMMOGRAM SEGMENTATION METHODS

S. No	Method	Merits	Drawbacks
1	Thresholding	Detection of masses and microcalcification	Sensitive to the threshold intensity value
2	Region Based	Tissue pattern classification	Computational complexity is high
3	Fuzzy c means	Effective for high resolution images	Depends on initial cluster center
4	K-means	Locating masses, computational complexity is less	Depends on the initial number of clusters
5	Markove fields	Representing the image spatial contest	Time of maximization process is expensive
6	Artificial neural network	Simultaneously identifying the background and the pectoral muscle	No evaluation of the background segmentation result
7	Watershed	Fast and produce complete division of image in separated region	Over segmentation
8	Edge detection	Detect breast boundaries	Computation time is more

V. CONCLUSION

Digital mammography screening approaches can enable early detection of breast cancer which reduces the mortality. There are lots of techniques developed for the detection and classification of masses. This paper discusses the commonly used mammogram image segmentation approaches for the early detection and diagnosis of breast cancer. Each method discussed in this paper has its own advantages and disadvantages and any methods can be selected based on the application.

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