TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol. 12, No. 8, August 2014, pp. 6211 ~ 6216
DOI: 10.11591/telkomnika.v12i8.6148

A Novel Approach for Tumor Detection in Mammography Images

Elahe Chaghari[1], Abbas Karimi*[2]
Department of Computer Engineering, Faculty of Engineering, Arak Brach, Islamic Azad University, Arak 38181-46775, Iran
*Corresponding author, e-mail: elahe.chaghari@gmail.com[1], akarimi@iau-arak.ac.ir[2]

Abstract

Breast cancer is one of the major causes of death among women in recent decades. Screening mammography is currently the best available radiological technique for early detection of breast cancer. In recent years, several methods have been used for automated tumor detection in mammography images. In some methods, due to a variety of processing and multiple operations on images, there are many computational complexities and much time overhead. In other methods the recognition accuracy is relatively low. In this paper, a new method to detect cancerous lesions in mammography images is presented using cellular learning automata algorithm. Cellular learning automata algorithm is well suited for image processing, because it is cellular and belongs pixels like an image. Distributed performance and parallel processing properties of this method has optimal results in image processing. Experimental results show the effectiveness of the proposed method.

Keywords: *medical image processing, mass detection, cellular learning automata*

1. Introduction

Breast cancer is one of the most common cancers among women all over the world. In the West, 10 percent of women survive with breast cancer and it forms about 19 percent of death rates resulted from cancers. About one out of every eight women in America is diagnosed with breast cancer in her lifetime [1]. in Iran, breast cancer ranks fifth in cancer deaths among women [2].

Since the cause of this cancer is unknown, it has long been considered important by clinicians and researchers, and that's why in many cases, breast cancer is not diagnosed until the advanced stages. This leads to use the imaging techniques besides the screening programs. Many methods have been used for breast imaging including: mammography, sonography, and MRI [3]. Among these methods, Mammography has been used more, due to some properties such as the possibility of lesion detection before doctor's detection in the clinical examination and before being visible on sonography images [1].

In the recent years, the technology used in the medical devices has been developed enormously and these devices provide complete information on the physical condition of the patient. Because of this, reconstruction and image processing techniques are highly regarded by researchers.

In mammography, due to the low contrast of images and also because of the fact that these images are often noisy, image detection is facing some challenges. Studies have shown that the sensitivity of human eye to interpret a large volume of images decreases with the increasing number of cases analyzed especially that, in the most majority of the cases, mammography images do not present obvious and visible signs which attest the existence of a tumor. Considering these aspects, the development of such computer aided diagnosis systems (CAD systems) to help early detection of breast cancer is very important and helpful; they would analyze mammograms and highlights only the abnormal areas [4].

According to the research, the number of false negative diagnoses in mammography reports in Iran is also more than twice the acceptable level [2]. Hence, providing a method to help radiologists and other physicians in detection of this disease appears necessary.

The purpose of this study is to provide a method for early detection of breast cancer, independently of the radiologist, and also to decrease the rate of false negative detection.

Received April 27, 2013; Revised June 1, 2014; Accepted June 15, 2014

The first step in image processing is the preprocessing stage. At this stage, the images with poor quality are enhanced. Shi *et al* [5], used Bayesian methods and wavelet techniques for reconstructing images and enhancing their quality. Changizi *et al* [6], proposed a method in which firstly threshold algorithm and secondly region growth algorithm are used to separate segments of the image. Saheb Basha *et al* [7], used morphological operators (including erosion, dilation, opening, and closing) for image segmentation and fuzzy C-means clustering method for pattern recognition and classification of masses. Mencattini *et al* [8], used two-dimensional wavelet to detect cancerous tumors and also applied the gradient and Laplacian filters to reduce noise. They combined two-dimensional wavelet with erosion and dilation of morphological operators to improve the segmentation methods. Cheng *et al* [9], used fuzzy logic to detect micro-calcification type of cancerous lesions in mammography images. Wang *et al* [10], proposed a method to detect breast cancer using support vector machine (SVM). Zheng *et al* [11], presented a new algorithm combining artificial intelligence techniques and the Discrete Wavelet Transform (DWT).

In this paper, a cellular learning automata algorithm is used to extract features and detect cancerous lesions.

2. The Proposed Method

The proposed method is shown in the following steps:

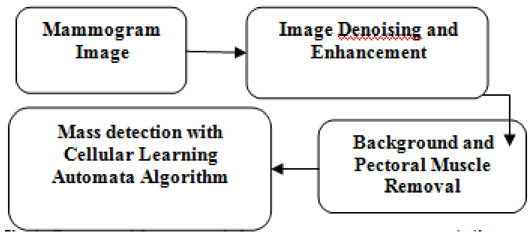


Figure 1. Proposed Framework for Mammogram Segmentation

2.1. A Database of Mammograms

The UK research group has generated a MIAS (Mammographic Image Analysis Society) database of digital mammograms. The database contains left and right breast images of 161 patients. Its quantity consists of 322 images, which belongs to three types such as Normal, benign and malignant. The database has been reduced to 200 micron pixel edge, so that all images are 1024 x 1024.

2.2. Image Denoising and Quality Enhancement of Image

Due to low contrast of mammogram images, it is difficult to detect signs such as masses, so before doing the main operation of image processing, the noise must be removed and image must be enhanced. For this, a combination of morphological operators was used.

2.3. Background and Pectoral Muscle Removal

As a preprocessing step, the breast area is separated from the background image. This saves the processing time and also the memory space.

The margin of some database images contains labels and frills and the degree of brightness of lateral muscles and the masses is close together. Because of these, in the next phase of research, frills and lateral muscles of the breast are detected and removed from the image.

Because of the large size of mammography images, a high volume of calculations required to find the damage and lesion areas, thus by reducing the area under study, image processing will be done more rapidly. so image sizes were reduced to 256* 256.

Then, using the threshold method and “find” and “bwlabel” MATLAB functions, labels and frills of image are eliminated [12].

2.4. Mass Detection with Cellular Learning Automata Algorithm

The main idea for using CLA to segment regions is to use the adjacency relation among regions for better segmentation. To do so, it is assumed that each image pixel is mapped to a cell in automata and each LA related to its pixel in input image. Then, a dynamic structure LA with L_R-ε_P learning algorithm [13] is allocated to each cell of CLA and Moore neighborhood is considered for the cells. Each learning automaton takes eight actions. Each action is related to eight neighbors of the central LA in a 3×3 adjacency which has a selection probability. Selection probability of each action shows the similarity of the central pixel to its neighbors. Selection of an action by central LA means that the central pixel in input image and the selected neighbor lie in the same region.

For receiving an award from the environment, each selected action increases its selection possibility for the next steps and reduces the other action selections and for receiving penalty from the environment, it reduces its selection possibility for the next steps and increases the selection possibility of the other actions.

A law which will be used to calculate the reward or penalty is that at first the brightness distance of pixel in a cell to all its neighbors is calculated [14].

$$D_i (x,y) = |I(x,y) - I(x_i,y_i)| \quad i= 1..8$$

The mean of these intervals is calculated and displayed with D_M (x, y). The law applied to this cell is:

$$C\times D_i (x,y) \leq D_M(x,y) \quad \text{Reward} \tag{1}$$

$$C\times D_i (x,y) > D_M(x,y) \quad \text{Penalty} \tag{2}$$

After determining the list of neighboring cells, the dye release operation occurs those pixels located on a segment are closer together in terms of color. To do this, the following formula is used:

$$I'(x,y) = \frac{\sum_{i=1}^{|L(x,y)|}(\mathrm{Wi} \times I\{Li(x,y)\})}{\sum_{i=1}^{|L(x,y)|}\mathrm{Wi}} \tag{3}$$

Where I is the input image, I' is the output soft segmented image, L(x,y) is the list of chain elements corresponding to pixel at location (x,y), |.| is the number of chain elements, L_i is the ith chain element and w_i is the weight related to the ith chain element which determines the effectiveness ratio of the ith chain pixel. Weights wi are designed to have an descending behavior. This is true and significant that the initial chain elements is more important and must have higher weights and the final chain elements are less important and must have lower weights.

```
CLA Algorithm:
Initialize the probability selection function
Repeat
Select an action using its probability selection function
Execute action on the environment
Receive cost/reward for previous action
Update probability selection function
Until stopping condition
```

Figure 2. Generic Pseudo-code for the CLA Algorithm

This cycle continues until a stop condition. Finally, using a threshold, the final step of integration phase was started and the mass is separated from the segmented image.

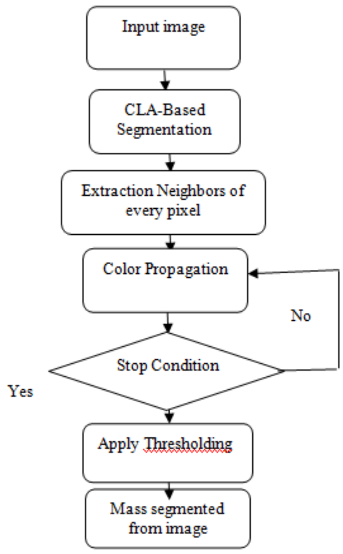


Figure 3. Overall Structure of Proposed Segmentation Method

3. Experimental Results

The proposed method was carried out on a 2.67GHz processors with 4 GB RAM on Windows 7 platform and MATLAB R2011b have been used. The proposed algorithm was tested on MIAS dataset. The Moore neighborhood with r =1 has been considered for CLA cells.

In the case of mammographic image analysis, the results produced using a certain method can be presented in a few ways. The interpretation being mostly used is the confusion matrix .this matrix consists of true negative (TN), false positive (FP), false negative (FN) and true positive (TP).

There are some often mentioned terms such as accuracy, sensitivity, precision. In this research, sensitivity is used for verify of proposed method.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (4)$$

In the following, results of the proposed method implementation and comparing it with other method with the same image database are presented.

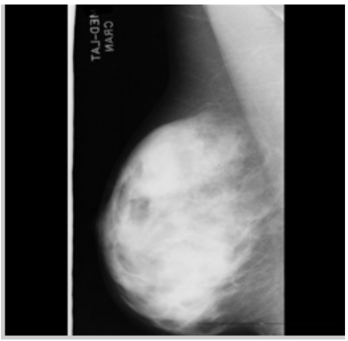
Table 1. Result of Implementing the Proposed Method on 25 Images of MIAS Database

FN	FP	TN	TP	The number of images has been processed with 25the proposed method.
1	2	2	20	25

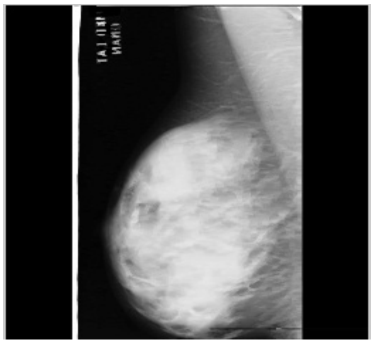
$$\text{Sensitivity} = {}^{20}/_{21} = 0.95 \quad (5)$$

Table 2. Result of Implementing the Proposed Method on 25 Images of MIAS Database

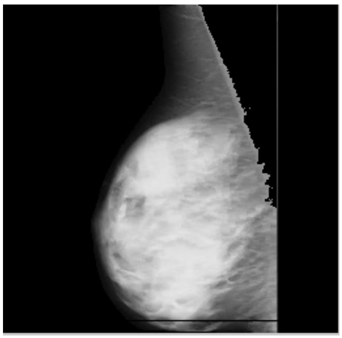
Sensitivity	Year	Author	Methods
92	2012	Hussain et al.(15)	A Comparison of Different Gabor features for Mass Classification in Mammography
95	2014		Proposed Method



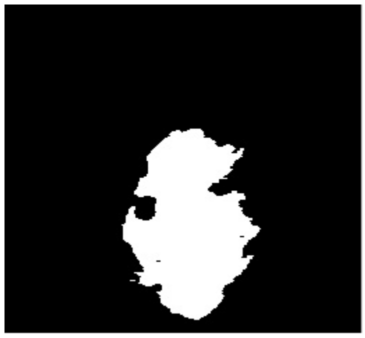
Original Image



Denoised Image



Pectoral muscle removal image



Mass Detected

Figure 4. Result of the Proposed Method

4. Conclusion

In this paper, cellular learning automata algorithm is presented for mammography image processing and detection of masses. The purpose of this research is to present a method for early detection of breast cancer and also independently of the radiologist in detecting and reducing the number of false detections (especially reducing the number of false negatives, which has a high cost due to exclude the patient from treatment cycle).

To evaluate the proposed method, 25 Images of MIAS database were analyzed, work output shows the Sensitivity of 95 percent. Due to the high Sensitivity and low number of false negatives in the detection, the result is acceptable.

Studies show that using intelligent methods for image preprocessing can improve the outcome. So the next step in continuing this research can be presenting an optimizer algorithm to enhance image quality and better removal of the pectoral muscled in the mammogram images.

References

[1] Schwartz. Schwartz's principles of surgery. Editor. 2010; 8.
[2] M HH. Comparing mammography and sonography reports with pathology reports of malignant and benign breast disease. *Breast Diseases.* 2009; 2(2).
[3] Jochelson M. Advanced Imaging Techniques for the Detection of Breast Cancer. *American Society of Clinical Oncology*. 2012.
[4] I Brodie RAG. Radiographic information theory and application to mammography. Med Phys. 1982; 4.
[5] Jinglun Shi ZS. Image resolution enhancement using statistical estimation in wavelet domain. *Biomedical Signal Processing and Control*. 2012.
[6] Changizi V GM, Arab Kheradmand Application of computed aided detection in breast masses diagnosis. *Indian Journal of Cancer*. 45(4).
[7] S Saheb Basha DKSP. Automatic Detection Of Breast Cancer Mass In Mammograms Using Morphological Operators And Fuzzy C-Means Clustering. *Journal of Theoretical and Applied Information Technology*. 2009.

[8] Arianna Mencattini MS. Mammographic Images Enhancement and Denoising for Breast Cancer Detection Using Dyadic Wavelet Processing. *IEEE transactions on instrumentation measurement*. 2008; 57(3).
[9] Heng-Da Cheng YML. A Novel Approach to Microcalcification Detection Using Fuzzy Logic Technique. *IEEE transactions on medical imaging*. 1998; 17(3).
[10] Defeng Wang L, PhengAnnHeng. Automatic detection of breast cancers in mammograms using structured support vector machines. *Neurocomputing.* 2009; 72.
[11] Chan LZaAK. An Artificial Intelligent Algorithm for Tumor Detection in Screening Mammogram. *IEEE transactions on medical imaging*. 2011; 20(7).
[12] R Subash Chandra Boss KT, D Arul Pon Daniel. Automatic Mammogram image Breast Region Extraction and Removal of Pectoral Muscle. 2013.
[13] Meybodi MRBH. Cellular Learning Automata and It's Applications. 2003.
[14] AA Abin MF, S Kasaei. *Skin Segmentation based on Cellular Learning Automata.* 6th International Conference on Advances in Mobile Computing & Multimedia (MoMM2008). 2008.
[15] Muhammad Hussain SK, Ghulam Muhammad, George Bebis. *A Comparison of Different Gabor features for Mass Classification in Mammography*. Eighth International Conference on Signal Image Technology and Internet Based Systems. 2012.