Automated Edge Detection of Breast Masses on Mammograms

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***Abstract*— Edge of a breast mass is one of the indicators of breast abnormality detection. In a mammogram, round and circumscribed masses indicate benign changes and malignant masses usually has speculated (irregular) boundary. The paper has encountered a fundamental problem of active contour model which was first proposed by Kass et al. The problem encountered here is generation of initial contour points manually selected by users. Thus the positions of initial contour points will vary with human perspective, which is very difficult to identify actual and accurate contour points. To overcome this problem to some extent, sobel edge detection method is used as a prior step of active contour model. Experiments have been tested on a dataset of 160 mammograms collected from Mini-MIAS benchmark database and compared with sobel edge detection method. In experiments, 92.5% segmentation accuracy has been obtained with sensitivity 93% and 85% specificity where the sobel edge detection method shown very less segmentation accuracy of 84% with 91% sensitivity and 50% specificity. Time complexity and detection error have been also analysed for proposed method, ideal high pass filter, sobel edge detection, hough transform and active contour model.**

***Keywords*— Breast cancer; Mammogram; Edge detection; Greedy active contour model; Automated segmentation.**

I. INTRODUCTION

Cancer that forms in the breast is the most life threatening disease among woman. It has become a most important health issue in the world more than the past 50 years, and its occurrence has increased in recent years. It happens to over 8% women during their lifetime [1]. The necessity for early detection of breast cancer is highlighted by the fact that incidence rates for breast cancer is one of the highest among all cancers according to the American Cancer Society which quotes a morbidity of 2,30,000 and a mortality of 40,000 according to the latest figures gathered for the American population. Currently, the most frequently used method for breast cancer detection is mammography and also it is known as the gold standard for breast cancer detection. German surgeon Albert Salomon (1913) was the first researcher to use mammography to detect breast cancer. This method involves low-dose X-ray (30-150 kilo voltage peak) imaging of the breast. Screening mammography examinations are performed on asymptomatic women to detect early, clinically unsuspected breast cancer [1]. The sensitivity of mammographic screening differs with image quality and expertise of radiologists. To balance this variability and to make the diagnostic procedure standard, attempts are being made to develop automatic techniques for diagnosis breast cancer. Microcalcifications and masses are two important early signs of the diseases [2]. The characteristics of the edges of a mass are able to indicate the presence of an abnormality. It has been seen in the paper of Campanini et al. (2004) [4] that they used an SVM-based featureless approach for mass detection in digital mammograms. Instead of extracting features from ROIs, the authors used a multiresolution, the wavelet representation to codify the image with redundancy of information. Two SVM classifiers have been used in their approach. They conducted experiments with 512 images containing 312 malignant tumors and 200 normal images from the DDSM database. The authors reported that the algorithm achieved nearly 80% accuracy true positive detection with a false positive rate of 1.1 marks per image for malignant tumors. In the year 2004, Joo et al. [5] presented a computer-aided diagnosis (CAD) algorithm to detect malignancy on ultrasonography (US) features and artificial neural network (ANN). The accuracy of ANN classifier has been measured on 584 histologically confirmed cases containing 284 malignant mass and 300 benign breasts mass. The features have been extracted from US images through digital image processing with a relatively simple segmentation algorithm. And they applied to the region of interest, which has been selected manually. The ANN classifier was then used to classify depending on five morphological characteristics like edges, shapes and darkness of a nodule. Their obtained accuracy was 91%. In the year 2007 Yuan et al. [7] utilizes a geometric active contour model and RGI-based segmentation method for automatic delineation of lesion boundaries on digital mammograms. They have used a full-field digital mammography database with 739 images, and then compare their proposed method with normal region growing method. With the threshold value of 0.4, they showed that 85% images were correctly segmented, where only 69% and 73% images were correctly segmented through manual region growing. After literature review of different cited papers it has been seemed that edge detection of masses is essential to identify breast abnormality. An edge of an image corresponds to the object boundary. They are pixels where the brightness or intensity of the image changes abruptly. If the intensity of a

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pixel is varying greatly from its neighbors then, it may indicate an edge. If the intensity of a pixel is similar to its neighbors, then there is no edge [3]. There are a number of edge detection methods in image processing. From these several methods ideal high-pass filter, sobel edge detection, hough transform, active contour model has been studied and analyzed. After analyzing these methods, two methods have proved the highest efficiency. They are sobel edge detection and active contour model. But the fundamental problem of active contour model for medical image analysis is initial contour points generation. The main contributory step of this paper is the development of a computationally efficient and automated edge detection method for detecting the edges of breast masses on mammograms. In this automated technique, sobel edge detection has been used to initialize the initial contour points for active contour model to segment the breast masses automatically. The numerical analysis of this automated technique has been also performed. After analysis, this new method has been also compared with other edge detection methods and then applied to Mini-MIAS database to segment breast masses. The rest of the paper are organized as, the automated method has been illustrated in section 2 and the experimental results, numerical analysis and performance evaluation of the proposed method with other methods have been given in section 3.

II. METHODOLOGY USED

Detection of true edges in a given image is the major problem in image processing. The process of identifying and locating clear discontinuities in an image is known as edge detection. These discontinuities of image intensities are abrupt changes in pixel intensity which characterize contours of objects in a scene. Mainly 2-D filter operators are used to detecting edges. They are used to convolve the image, after convolving they provide an edge if intensity discontinuities are present in images and it returns no edges in uniform regions. There are an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges. The major obstacles in case of edge detection are edge orientation, the presence of noise in image, blur edges. In an image both the noise and edges have the same intensity value; therefore it is very difficult to detect edges in the presence of noise. The noise can be removed by using different filtering techniques, but these filtering techniques make edges hazed and distorted. Therefore the result of edge detection is more inaccurate, and edge detection method will become computationally inefficient. All edges do not involve an abrupt change in intensity. The operator needs to be chosen carefully in such a way that edge detection method must be computationally efficient. Regarding these problems of edge detection, the aim of this paper is to perform an analytical comparison of various edge detection techniques.

It has been observed after numerical analysis and from experimental results that active contour model and sobel edge detection methods are two computationally efficient ways of contour detection. But sometimes sobel edge detection method gives disconnected edge points for irregularly shaped objects. One of the major disadvantages of active contour model is that

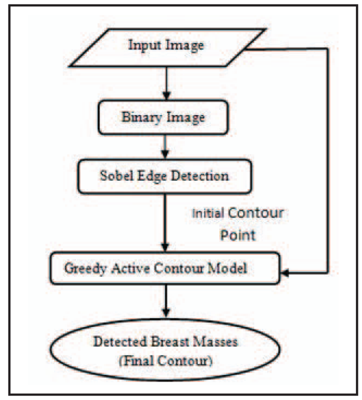

Fig. 1. Block diagram of proposed method

it can’t detect edges if it is initialized too far from the object boundary and also active contour model needs to initialize initial contour points manually by the user, which will be a problematic if the user is unfamiliar. The shortcomings of these both methods can be reduced by initializing the initial contour points using sobel edge detection method for active contour model. Fig. 1, represents the block diagram of this automated technique. The steps of the automated method have been described as follows.

A. Binary Image

Mass lesion boundaries in mammography images are complicated and, therefore, it is not guaranteed that the edge of the mass boundary corresponds to abrupt intensity changes. Regarding these problems, the automated method requires converting the image into a binary image. Here, region growing method has been used. In region growing at first one seed point is selected then all the pixels which have similar intensity (here, between intensity 50) as the seed point are assigned a binary value [3]. This way image has been converted into a binary image which highlights the edges of the input image.

B. Contour Initialization

In this automated technique, sobel edge detection has been used as a step for initial contour estimation for active contour model which yields an initial contour closer to the actual boundary if the mass. Sobel edge detection method is one of the basic edge detection methods in image processing. It works based on discrete approximations to differential operators. Differential operators are mainly used to compute the rate of change of gray values of images. Sobel edge detection method uses two differential operators, one for finding the x-directional changes, and another for y-directional changes. These two operators perform convolution operation with the input image. After convolution, sobel edge detection method gives the edges of the input image. But sometimes it has been observed that it can’t detect edges properly, and there are always disconnected points on the edge of the output image as depicted in Fig. 2. Here, to make a connected and smooth edge, active contour model is used.

C. Active Contour Model

In this automated technique, active contour model has been used to smooth the boundary delineated by sobel edge detection method and also to obtain connected edge points. Active contour model is quite a different edge detection method than traditional edge detection methods of image processing [12], [13]. About 27 years ago in 1988, Michael Kass, at first proposed a new method active contour model [14]. Since then a lot of researchers worked on this method and many of them proposed new ways of working with active contour model. In the year 1992, Williams and Shah proposed a new method to evolve active contour model, and this is known as greedy active contour model. This method starts with initial contour points. The snake evolved so that to enclose the target feature or to detect the boundary of interest. For each and every initial contour point it computes the energy function, i.e., the combination of points own internal energy and image energy (edge magnitude). The energy function of the snake is as follow [15].

1) Energy Function: The energy function of a snake is the combination of spline's internal energy due to bending, stretching an image's energy. These are denoted E_{int} and E_{image} in Equation (1) respectively [13]

$$E_{Snake} = \int_{s=0}^{s-1} E_{\text{int}}(\text{v(s)}) + \text{E}_{image}(\text{v(s)})\,\text{ds} \tag{1}$$

a) Internal Energy: Internal energy of a snake is the combination of its stretching energy and bending energy with weighted coefficient [12].

$$E_{\text{int}}(v(\text{s})) = \frac{1}{2}(\alpha(\text{s})\,|\frac{dv(\text{s})}{ds}|^2 + \beta(\text{s})\,|\frac{d^2v(\text{s})}{ds^2}|^2) \tag{2}$$

In Equation (2), the first order differential, dv(s)/ds, defines the energy due to stretching, which is the elastic energy since high values of this differential imply a high rate of change in that region of the contour. The first order differential is weighted by α(s), which controls the contribution of the elastic energy due to point spacing. Low values for α(s) implies that the point can change in spacing greatly. Higher values imply that the snake aims to attain evenly spaced contour points [13]. Here, the first order differential is approximated as the modulus of the difference between the average positioning of contour points (evaluated as the Euclidean distance between them), and the Euclidean distance between the currently selected image point v(s) and the next contour point [2]. It can be defined by the selection of an appropriate value of s for each contour point v(s) [13].

$$|\frac{dv(\text{s})}{ds}|^2 = \sum_{i=0}^{s-1} \frac{\|v(\text{i}) - \text{v(i+1)}\|}{s} - \|\text{v(s)} - \text{v(s+1)}\| \tag{3}$$

$$= |\frac{\sqrt{(x(\text{i})-\text{x(i+1)})^2 + (y(\text{i})-\text{y(i+1)})^2}}{s} - \sqrt{(x(\text{s})-\text{x(s+1)})^2 + (y(\text{s})-y(\text{s+1}))^2}\,| \tag{4}$$

In Equation (2), the second order differential $d^2v(s)/ds^2$ measures the energy due to bending i.e. the curvature energy. The second order differential is weighted by β(s), which controls the contribution of the curvature energy due to point variation. Low values for β(s) imply that curvature is not minimized, and the contour can form corners around its perimeter whereas high values predispose the snake to smooth contours [13]. The second order differential can be implemented as an estimate of the curvature between the next v(s+1) and previous contour points v(s-1) respectively in Equation (5) and Equation (6). The point in the neighbourhood of the currently inspected snake point is v(s) [13].

$$|\frac{d^2v(\text{s})}{ds^2}|^2 = |(\text{v(s+1)} - 2\,\text{v(s)} + \text{v(s-1)})|^2 \tag{5}$$

$$= (\text{x(s+1)} - 2\,\text{x(s)} + \text{x(s-1)})^2 + (\text{y(s+1)} - 2\,\text{y(s)} + \text{y(s-1)})^2 \tag{6}$$

b) Image Energy: Image magnitude of a pixel is the pixel value itself. Here, normalization is used to obtain a low value for high pixel value. Thus, the normalization can be obtained by Equation (7) [14].

$$E_{image} = \frac{Minimum\_Pixel\_Value - Magnitude}{Maximum\_Pixel\_Value - Minimum\_Pixel\_Value} \tag{7}$$

The automated method used the sobel detection method to initialize initial contour points then for each and every points energy functions are calculated. Every point will move to one of their neighbours who have the lowest energy. This process will continue for some iteration. So here manually initialization problem is reduced by initializing contour points with sobel and the problem of generating disconnected edge map by sobel edge detection method is solved using active contour model.

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Dataset Collection

In order to fully explore the proposed segmentation method, a set of 160 mammograms (15 Circumscribed masses, 7 ill-defined masses, 7 Speculated masses, 131 Normal) with resolution 1024×1024 has been analyzed. The mammograms have been collected from Mini-MIAS database [11].

B. Results of Active Contour Model

In active contour model, to start the main execution it needs to put initial contour points by operator. Thus it depends on various factors such as age of the operator, psychological factors such as fatigue or acquired habits etc. So the identified edge will vary for different operators and actual edge detection is difficult. The results of active contour model with manually initializing contour points have been depicted in Fig. 2.

C. Results of Proposed Method

Fig. 3, shows the results of proposed method and the results infer that the final output is a connected edge map. It means proposed automated method can reduce the problem of active contour model by sobel operator. The computational efficiency of the proposed method has been obtained by a numerical analysis based on the time complexity and also the detection error of this method. The experimental results have been also given. In proposed method, the value of elastic constant α is 1, curvature constant β is 1 and image energy constant γ as 1.2 has been taken. Here, the maximum number of iterations is set to 40 for the proposed segmentation methods. In Fig. 3, results of all successive steps of proposed

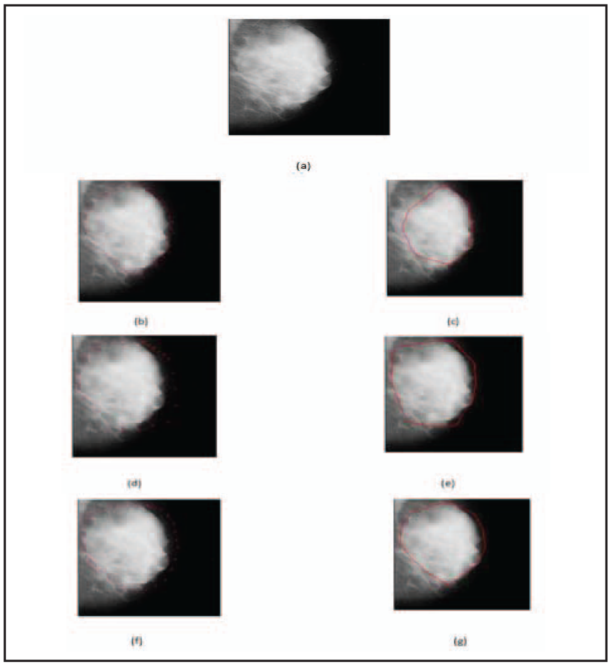

Fig. 2. Input Image (a), Different initial contour points (b), (d), (f) and final contour(c), (e), (g).

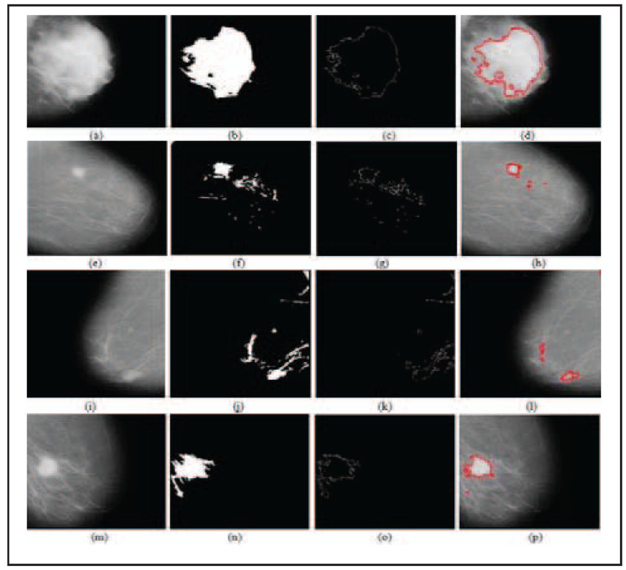

Fig. 3. Input images from collected dataset (a),(e), (I),(m) converted binary images (b), (f),(j), (n), outputs of sobel edge detection (c),(g),(k), (o) and outputs of active contour (d) , (h), (l) ,(p).

automated technique has been depicted. The performance evaluation of the proposed automated segmentation technique has been assessed by comparing the automated delineated contours with the outlines detected by traditional sobel edge detection methods. Performance evaluation of the proposed method has been done based on statistical measures such as accuracy, sensitivity, and specificity. TABLE I. contains these statistical measures of the proposed method on mammography dataset. The analysis shows that sobel edge detection method can detect 119 masses whereas proposed method can detect 131 masses correctly. Sobel edge detection method and proposed method can't detect 14 and 3 masses respectively. The proposed method can show 17 non-mass images and wrongly detect 9 non-mass images where sobel edge detection method can show 14 non-mass images and wrongly detect 11 non-mass images. The accuracy of the sobel edge detection method is 84% with 91% sensitivity and 50% specificity. On the other hand, the automated method impressively shows 92.5% accuracy with 93% sensitivity and 85% specificity. Fig. 4, depicts the graph of the performance of the proposed method.

D. Performance Evaluation of Proposed Method with other Methods

The numerical analysis of different edge detection methods has been done based on their time complexity and detection error. In computer science, algorithms quantify or express the amount of time taken by algorithms to run as a function of the length of the input string is known as the time complexity of algorithms. If a method has low time complexity, which means it is highly computationally effective. For standard binary shapes, detection error is the differences between the desired outcome (D) and the actual outcome (A). This difference can be computed by NORM. Here, 2 Norm has been used. Detection error can be computed by using Equation (8) and Equation (9) [15].

$$E = \frac{\| x - y \|}{\| x \|} \tag{8}$$

$$E^1 = \frac{\| x - y \|}{\| y \|} \tag{9}$$

The Equation (8) and Equation (9) are known as the relative detection error. Relative detection errors are mainly used when the amount of the difference is needed with respect to the original quantity [15].

Analysis of different edge detection techniques based on their time complexity and detection errors on standard shapes are shown in TABLE II. Here, ideal high pass filter [17], sobel edge detection method [3], hough transform [16], active contour model [14] have been analyzed. Edge detection method with low detection error is called as the high computationally effective method. It has been seen in the numerical analysis that automated technique has less time complexity than hough transform. The proposed automated technique has less detection error than all of the edge detection methods discussed in this paper. From this analysis, it is proved that automated technique is one of the efficient ways of edge detection.

IV. Conclusion

A new automated edge detection technique has been developed which includes an initial sobel edge detection and active contour model. Evaluation with a 160 datasets of mammogram images has shown that the proposed automated edge detection method is superior to sobel edge detection method. It has been seen after comparative study with different edge detection methods that the proposed method is a computationally efficient way of edge detection.

TABLE I. PERFORMANCE GRAPH OF AUTOMATED TECHNIQUE AND COMPARISON WITH SOBEL EDGE DETECTION

Method	True Positive	False Positive	True Negative	False Negative	Sensitivity	SpecifIcity	Accuracy
Sobel Edge Detection	119	11	14	14	91%	50%	84%
Proposed Method	131	9	17	3	93%	85%	92.5 %

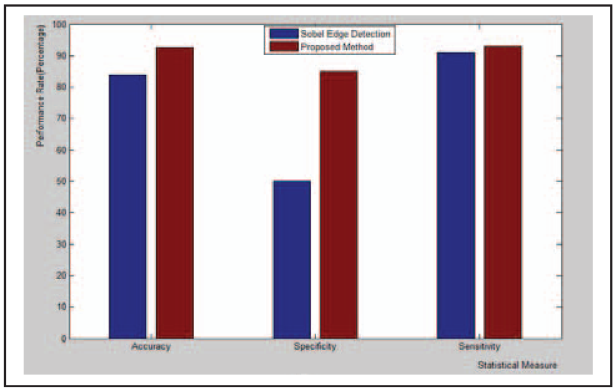

Fig. 4. Performance graph of automated technique and comparison with sobel edge detection

TABLE II. ANALYSIS OF PROPOSED METHOD WITH OTHER METHODS

Sl.No	Edge detection methods	Time complexity	Detection error 1(E)	Detection error 2(E[1])
1	Ideal high pass filter	Big-O(mn) m, n= the dimension of the image	0.9962	11.6079
2	Sobel edge detection	Big-O(m n) m, n= the dimension of the image	0.1595	0.1613
3	Hough transform	Big-O(p^2m^2wh) w, h= the row and column of the image. p= number of edge points. m= number of angles	0.9999	2.2017
4	Active contour model	Big-O(m n) n= Number of points of the snake contour. m=Number of neighborhood.	0.238	0.292
5	Proposed method	Big-O(m n) n, m= dimension of the input	0.1529	0.1588

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