Volume 66, Issue 2, 2022

Journal of Scientific Research

of

The Banaras Hindu University

Approach For Segmentation of Masses in Mammographic Images Based on A Change in Grow Cut

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Abstract. Throughout the world, breast cancer is common cancer in women that contribute to high death amongst women. The early diagnosis and corresponding treatment can increase the possibilities of survival. In contrast, the challenging task is to detect the mass early in mammographic images, which is difficult due to noise and contrast. Mammography is the most capable technique used by radiologists frequently, which helps detect abnormal mass at an early stage; it is one of the methodologies to identify breast cancer. Here, a system is used to detect the tumor, with a modification in the grow cut algorithm. A new method is suggested based on segmentation by changing the modified grow cut algorithm by improving the region of interest. A modified grow cut algorithm has changed seed selection in mammogram images from manual into the semiautomatic way and has worked on non-defined borders. The earlier algorithm grows the region of interest only for the neighbor of current pixels and, consequently, a neighbor. Still, a change is made in the methodology for growing the region of interest within the class and between a neighbor cell's neighbors. This will ensure to get a more effective segmented area for abnormal mass than the previous method. The proposed technique is evaluated with the help of the mini M.I.A.S. database by considering circumscribed lesions, speculated lesions. Through result analysis, it is clear that the proposed technique gives better results for speculated, circumscribed lesions based on a comparison of ground truth images and segmented results.

Keywords: Breast cancer, Grow cut algorithm. Lesion, Mammography, Radiologist, Segmentation of image.

1 Introduction

Breast cancer statistics are alarming all around the world, and it is the second leading cause of death in women with cervical illnesses. This cancer has become a major problem all across the world, especially in India. According to Globocan's analysis, one out of every 28 women in India is likely to develop breast cancer.

Microcalcifications (MC) are very small calcium deposits that can appear in groups or patterns and are linked to extracellular activity in breasts. Breast cancer is classified as either invasive or non-invasive. The key to surviving breast cancer is early diagnosis. Mammograms are breast X-rays that can identify cancers at a preliminary phase before they are felt or recognized in other ways. The breasts are squeezed between two hard surfaces during mammography to spread out all the breast tissue. Then, using an X-ray, black-and-white photos of your breasts are captured and viewed on a computer screen by a doctor looking for indications of cancer.

A poll conducted by the American Cancer Society is given in table 1. According to the report, 252,710 instances of invasive breast cancer were discovered in women in 2017 and 2,470 cases in males. In addition, more than 63,410 instances of in-situ breast carcinoma were discovered among women. Breast cancer struck 40,610 women and 460 men in 2017. [1]. Mammography has become the most sensitive method for detecting breast cancer and the most feasible method for screening and follow-up. Computer-aided identification can be used to assist radiologists to detect unexpected region findings on mammograms. These programs simply serve as a second reader, with the ultimate decision resting with the radiologist. The use of CAD screening technologies has also been found to improve radiologists' breast cancer accuracy rates.

Table1. Age-specific Breast Cancer Probability U.S. Women

Age of person	Probability in ten years	or 1 in
20	0.1%	1,567
30	0.5%	220
40	1.5%	68
50	2.3%	43
60	3.4%	29
70	3.9%	25
Lifetime risk	12.4%	8

The following is the layout of the paper. Section 2 examines several current techniques for segmenting and classifying malignant masses in mammography images for a brief period. The suggested method for detecting the tumor is depicted in Section 3. The results and execution outcomes are shown in section 4, and the conclusion is given in section 5.

2. Related Work

Improving the accuracy of tumor identification in mammographic images is one of the tedious tasks because of the variation in the contrast of mammographic images. Many methods have been described in the related work; Shen-Chuan et al. planned two sophisticated feature extraction methods, optical density transformation and G.L.C.M. [2]. Aziz Makandar et al. [3] have projected a way to segment the mass for which they have combined different morphological operations, watershed transform, and segmentation based on active contour. Ismahan et al. [4] also worked on mathematical morphology to detect mass in mammographic images. A new approach is given by Nadia smaoui et al. [5] and has described

DOI: 10.37398/JSR.2022.660201

an original method that is based on specific steps such as preprocessing to remove noise than using morphological operators for detecting the tumor. Most of the work focuses on eliminating noise from the image or enhancing mammograms; this work is found in [6-8]. Where paria yousefi[6] used wavelet transform to improve image enhancement. They decomposed the image into different sub-bands, followed by manipulating them with mathematical morphology and filtering concepts. P.S. Vikhe et al. [7] have worked on an enhancing contrast-based approach for mammogram images depend on adaptive threshold and wavelet; also, NijadAI-Najdawi et al. [8] have applied an optimal combination of various enhancement methods and classification of the tumor. Kartikeyan ganesan[9] has given a detailed review of cancer detection in mammogram images. In medical image processing, segmentation is vital to identifying the tumor correctly; so many methods have been projected based on region growing image segmentation methods. Filipe et.al.[10] have proposed improving the Grow cut(G.C.) process based on automatic seed selection Hussein Samma et al.[11] have submitted similar operations of automatic mammogram mass detection. Grow cut methodology is having a base of cellular automata [18]. In one of the approaches pereira et.al. Has worked on mammographic image mass detection with the help of wavelet analysis and a genetic algorithm [19]. In medical image processing, segmentation plays a crucial role in detecting cancer masses; a study of these is depicted by R. Merjulah [20]. In the [12] paper, Yanfeng et al. have given an overview of current development in the detection and mass classification of breast cancer; they have given more attention to abnormality detection and classification. In [13], Tang et al. have given recent advances in diagnosis in CAD systems. In [15], brief medical image segmentation techniques are described, along with that some of the limitations and advantages are given. Melouah et al. [16] Have worked on mass segmentation in mammograms based on seed selection; they have worked on both ways manual and automatic selection of seed pixel. A graph cut method is a segmentation approach based on graphs; these are effective in clinical applications. In [17], the author has worked on the graph cut method. Most of the authors have worked on region-growing methods for the segmentation of images [21-24]. Considering all the work done by researchers, a method is provided to improve the grow cut algorithm by a change in the region grow technique where considering neighboring pixels to grow the region and a neighbor of neighbor to get a better area of R.O.I. This manuscript is prepared as follows in Section 1 and 2 Describe Introduction &Related Work, in the next part, Section 3. Elaborate methods to improve the segmentation based on improvement over Modified Grow cut (MGC). The result is presented in section 4, while the conclusion is described in Section 5.

3. Methodology

One of the applications of image processing is in medical images, where one of the essential tasks is segmentation. In image processing related to medical, especially in tumor detection, the radiologist may be unable to detect some part because of noise and glandular tissue. Because of dense tissue, also they lack to identify the tumor correctly, which may lead to the substantial possibility of False Positives. The proposed method work is represented in Figure 1. This shows a block diagram for working development.

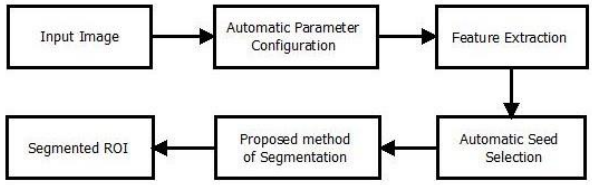

Figure 1. Block diagram for a proposed working strategy

3.1 **Modified Grow Cut**

The proposed method is based on a modified grow cut algorithm; It is one of the specific algorithms based on segmentation technique. This algorithm will help segment the image with relatively complex borders. This algorithm involves the process of the region grow where the concept of seed pixels is used. Here this process starts by labeling the set of pixels. All pixels will get labeled based on the intensity of the grey level. The picture can be visualized as a grid of cells since this algorithm is based on cellular automata. Each cell in this grid has some strength because the region growing approach is focused on the brightness of these pixels. Now, the determined cell gets attacked by the neighbor cell, where the label gets changed.

On the other hand, if the attacker cell's strength is less than that of the protective cell, the protective cell label does not change. Otherwise, that cell inherits the tag of attacker cells, and this will continue until it converges. The Gaussian fuzzy membership function is responsible for a region for each cell's attack in a modified grow cut algorithm.

Algorithm 1 (Modified grow cut)
Procedure Modified GrowCut (x, l)

$\mathrm{lb_c = lb_{ob}}$
$\Theta_c = 1$
for all $x \in X$, do
$\mathrm{lb}_x^{t+1} \leftarrow \mathrm{lb}_x^t$
$\psi_x^{t+1} \leftarrow \psi_x^t$
Calculate $\psi_{M,x}^t$
for all $y \in N(x)$, do
Calculate $\psi_{M,y}^t$
If $g\left(\left\|\vec{c}_x - \vec{c}_y\right\|_2\right) . \psi_{M,y}^t > \psi_{M,x}^t$ then
Calculate $\mathrm{lb}_{M,x,y}^t$
$\mathrm{lb}_x^{t+1} \leftarrow \mathrm{lb}_{M,x,y}^t$
$\psi_x^{t+1} \leftarrow g\left(\left\|\vec{c}_x - \vec{c}_y\right\|_2\right) . \psi_{M,y}^t$
If loop End
For loop End
For loop End
Return lb
End of procedure

The function g is a decreasing monotonic function; the $\max\|c\|$Showcase the max value for the vector of pixels in between attacker and defender cells.
The initialization is carried out concerning the expressions

$$\forall x \in X, lb_x = 0, \Psi_x = 0, lb_c = lb_{ob}, \Psi_c = 1 \quad (1)$$

Here x is part of a cell in space X; the cell x has the labels denoted by lb_x and strengths denoted by Ψ_x. For the mass in the center of seeds, the lb_c represents the labels, and Ψ_c defines the strength of the cell, respectively.

3.2 **Proposed Algorithm**

The notion of seed pixel is utilized in the modified grow cut method as shown in algorithm1, where the region expands depending on the evolution rule, with the selected pixel acting as an attacker cell and the surrounding cells acting as defender cells. As a result, if the attacker cell's strength is greater than the neighbor cell's, the neighbor cell receives the defender cell's label; otherwise, the defender cell retains its label. In this scenario, because the region increases linearly, focusing just the attacker cell and adjacent cells, the segmented section is inefficient; instead, the area must expand by considering these pixels as both inside and between groups. So that the task of choosing neighbor pixels is not limited to those in the immediate vicinity. Still, it will consider the neighbor of neighbor, and because of this, the final area is more effective.

Algorithm 2 (Proposed Method)

Procedure Proposed_Algo (x, l)
$lb_c = lb_{ob}$
$\psi_c = 1$
forall $x \epsilon X$ do
$lb_x^{t+1} \leftarrow lb_x^t$
$\psi_x^{t+1} \leftarrow \psi_x^t$
Calculate $\psi_{M,x}^t$
for all $y \epsilon N(x)$, do
Calculate $\psi_{M,y}^t$
If $g\left(\left\|\vec{c}_x - \vec{c}_x\right\|_2\right) . \psi_{M,y}^t > \psi_{M,x}^t$ then
Calculate $lb_{M,x,y}^t$
$lb_x^{t+1} \leftarrow lb_{M,x,y}^t$
$g = \frac{1}{1+\mathrm{Exp}\left(-(E-E')\right)}$
If Loop End
For Loop End
For Loop End
Return lb
Procedure End

Where E is the difference of strength between neighboring pixels. It can be represented as follow

$$\psi_p^{t+1} \leftarrow \psi_p^t \quad (2)$$

$$E = \sum_{i=1}^{k} \sum \forall x \in X \parallel C x - Cy \parallel^2 \quad (3)$$

First, the modified grow cut algorithm as shown in algorithm1 starts with seed pixels and labels some pixels relative to different classes. Later on, considering the gray level, all the other pixels are getting labeled. Each cell has the strength value when the seed pixel is getting dominated over the neighboring pixel if its strength is more and neighbor pixel get the same label as that of seed pixel; otherwise, it happens in the other way. In this manner, all the other pixels get labeled, and we get the region of interest. This process is getting repeated until the algorithm will not get converged. In this case, the seed cell's neighbor cell is considered, so getting limited to surrounding pixels only. After segmentation, it still gets some difference or error in ground truth image tumor and resulted in output image tumor. This can be minimized by the proposed method, trying to reduce that error rate by adding the energy function, represented in equation no. 3. This means the difference between neighbors of neighbors as the focus is on considering here not only surrounding pixels but also a neighbor of neighbor so going into the depth of these cells and covering the general area adequately.

4. Experimental Results

This part describes the helpfulness of the projected approach for the detection and classification of mammographic images. As in the grow cut algorithm, the search space for finding Region of interest is limited to the neighbor of seed pixels. There was some error in tumor detection, so to overcome this proposed approach, we have considered a neighbor of neighbor for labeling the pixels based on the region growing method. For performing the experimental work MIAS (mammographic image analysis society) database is used, which consists of information related to the data set's Ground-truth. The mini MIAS Database collects 322 mammogram images and deals with the Different views of this database, which have a dimension of 1024×1024 pixels [14].

In the modified grow cut algorithm, the seed pixel is selected automatically instead of manually selecting it; if we choose the seed manually, there might be more chances to have a manual error.

Table 2. Average values for all types of masses

	Wavelet	**Grow Cut Method**	**Modified Grow cut method**	**Proposed Algorithm**
E_Area	0.60 ± 0.29	0.72±0.29	0.34±0.31	0.31±0.31
EForm_Factor	0.36 ± 0.20	0.40±0.27	0.26±0.25	0.25±0.24
EPer	0.53 ± 0.27	0.63±0.29	0.27±0.25	0.25±0.25
EFX	0.37 ± 0.23	0.47±0.27	0.20±0.21	0.20±0.20
EFY	0.37 ± 0.22	0.47±0.27	0.20±0.21	0.20±0.20
Esolidity	0.14 ± 0.13	0.18±0.25	0.09±0.15	0.08±0.14
AOM	0.42 ± 0.25	0.38±0.24	0.58±0.24	0.60±0.24
Sensitivity	0.83 ± 0.31	0.91±0.26	0.82±0.22	0.91±0.27
Specificity	0.64 ± 0.34	0.59±0.22	0.84±0.18	0.87±0.04
BAC	0.73 ± 0.16	0.75±0.12	0.83±0.13	0.88±0.14

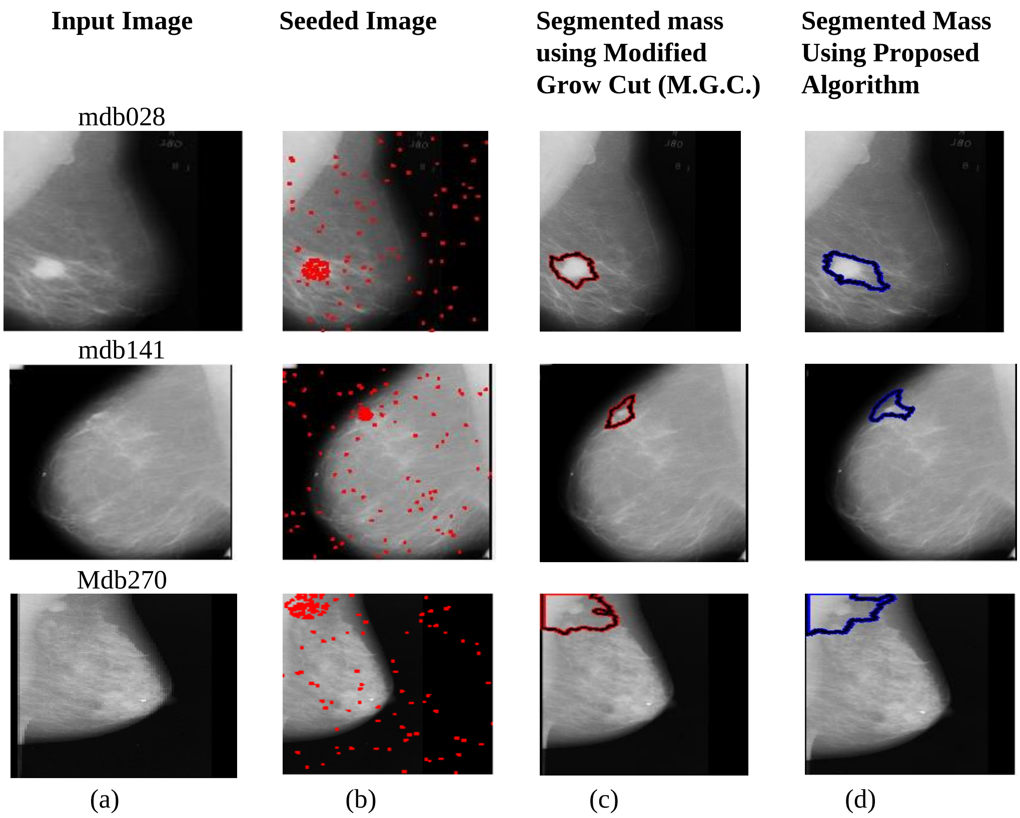

Figure 2 Mass segmentation for circumscribed images using M.I.A.S. Database a) Input Image b) Seeded Image c) Modified Grow Cut. d) Proposed algorithm

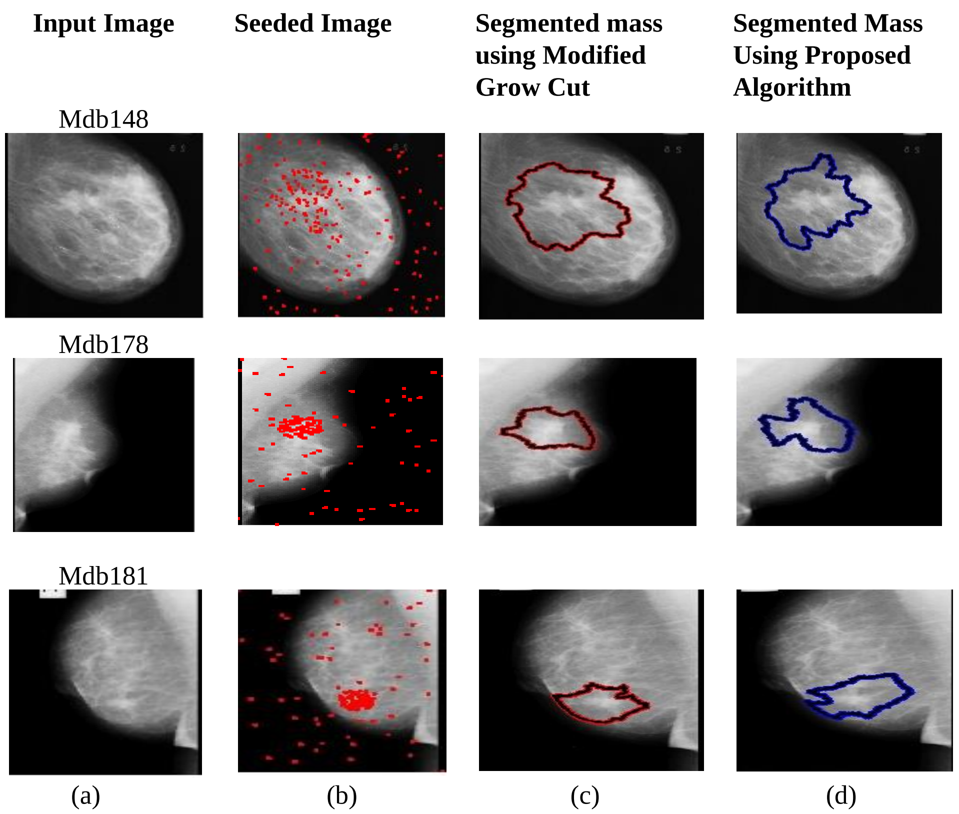

Figure 3 Mass segmentation for speculated images using M.I.A.S. Database a) Input Image b) Seeded Image c) Modified Grow Cut. d) Proposed algorithm

Table 3 Average value for all Circumscribed lesions.

	Wavelet	Grow Cut Method	Modified Grow cut method	Proposed Algorithm
E_Area	0.46 ± 0.27	0.67±0.31	0.39±0.36	0.38±0.36
EForm_Factor	0.39 ± 0.18	0.40±0.30	0.30±0.30	0.29±0.29
EPer	0.45 ± 0.30	0.60±0.30	0.33±0.31	0.33±0.31
EFX	0.28 ± 0.18	0.45±0.30	0.25±0.28	0.24±0.27
EFY	0.28 ± 0.18	0.44±0.28	0.23±0.28	0.23±0.20
Esolidity	0.13 ± 0.10	0.19±0.27	0.15±0.23	0.08±0.18
AOM	0.49 ± 0.25	0.43±0.26	0.53±0.29	0.54±0.28
Sensitivity	0.76 ± 0.32	0.90±0.29	0.77±0.30	0.91±0.27
Specificity	0.79 ± 0.25	0.62±0.24	0.86±0.14	0.88±0.04
BAC	0.78 ± 0.14	0.76±0.13	0.81±0.17	0.82±0.14

Table 4 Average value for all Speculated lesions

	Wavelet	Grow Cut Method	Modified Grow cut	Proposed Algorithm
E_Area	0.72 ± 0.25	0.83±0.23	0.38±0.38	0.37±0.34
EForm_Factor	0.38 ± 0.22	0.46±0.24	0.30±0.30	0.28±0.12
EPer	0.64 ± 0.23	0.71±0.27	0.33±0.31	0.30±0.21
EFX	0.47 ± 0.24	0.55±0.27	0.25±0.28	0.22±0.18
EFY	0.46 ± 0.26	0.43±0.28	0.23±0.28	0.23±0.27
Esolidity	0.18 ± 0.18	0.20±0.22	0.15±0.23	0.14±0.10
AOM	0.32 ± 0.22	0.30±0.21	0.53±0.29	0.64±0.22
Sensitivity	0.83 ± 0.33	0.92±0.23	0.77±0.30	0.98±0.07
Specificity	0.56 ± 0.34	0.54±0.20	0.86±0.14	0.87±0.13
BAC	0.69 ± 0.15	0.73±0.11	0.81±0.17	0.84±0.14

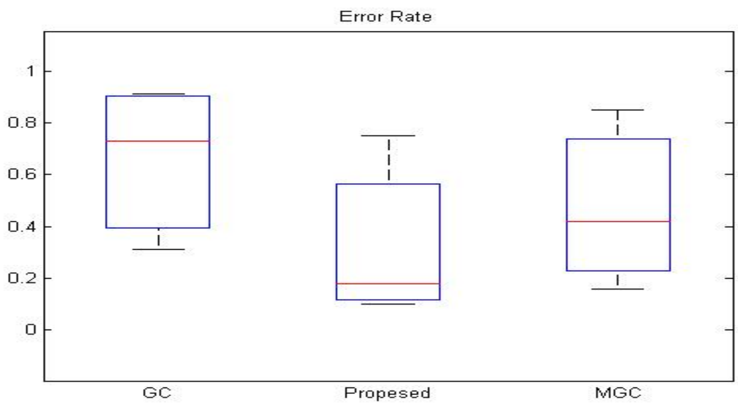

Figure 4. Chart for error rate analysis

Figure 2 illustrates mass segmentation for the circumscribed type of images using a modified grow cut and suggested method. Table 3 shows the average efficiency measurement results for circumscribed images in the same way that Figure 3 shows the segmentation for speculated images. Table 4 shows the average findings for the mass segmentation of speculated images. Overall, the suggested algorithm outperformed previous techniques, according to the results. The error rate is depicted in Figure 4; it is discovered that, when compared to the other techniques, the suggested method has the lowest error rate.

5. Conclusion

This work presents a unique technique for mammographic image segmentation based on the region growing idea, which improves on the modified grow cut algorithm. The suggested technique is separated into three steps: automated seed point selection, segmentation, and R.O.I. followed by a feature extraction procedure. Work is carried out using support vector machine classification, and overall performance is assessed using pictures from the M.I.A.S. database. The results are compared to established algorithms, and the radiologist is also concerned. The average balanced accuracy in the modified grow cut was 83.13 percent, whereas it was 88.14 percent in the recommended technique; similarly, sensitivity and specificity found in modified grow cut was 82.22%,84.18%

while in the proposed method it is 91.27%, 87.04% respectively. In future work, the focus will be on multi-objective optimization techniques for increasing the accuracy of mass detection and also try to reduce the overall time required for mass screening in the mammogram.

Acknowledgment: I want to convey appreciation to the people from the Department of Radiology, M.G.M. Medical College and Hospital, Aurangabad, M.S. India, for their support.

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