Segmentation of Pectoral Muscle in Mammogram Images using K-means and Region Growing

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Abstract: Breast cancer prevails to be one of the major cancer types in women worldwide. In the context of the prevention and early detection of breast cancer, it is necessary to conceive diagnostic aid systems to control tumor growth with very high precision and to give more effective treatments adapted to the pathological stage of the tumor. To achieve such a system, there is a need to firstly start with the pretreatment step which enhances the quality of boundaries and structures. Secondly, the segmentation step is needed to be performed on the pretreated images which consist of the pectoral muscle (PM) that is located in the upper corner of the mammography in the Medio-Lateral-Oblique (MLO) view. In this paper, we propose a novel approach to remove PM in MLO observations of mammograms. This approach is based on the ideas of clustering, region and edge. For implementation, experimentation and verification, the proposed technique has been tested on the digital mammography of Mini-MIAS database. DICE Coefficient and Structural Similarity measure have been used to find out the goodness of segmentation between the segmented regions and the ground truth. The proposed approach has proved to be effective and superior as compared to various existing techniques in the same context.

KEYWORDS: Breast cancer, mammography, pectoral muscle, k-means, region growing, segmentation, CAD.

1 Introduction

Breast cancer is a malignant tumor [1,-13] that originates in breast cells. The word "malignant" means the tumor that can spread (metastasize) to other parts of the body. Breast cancer is the most regular and invasive type of cancer among women. To decrease the rate of mortality, the prevention and early detection are essential and helpful for the success of treatment [14].

Mammography [13,15,16,11,17,18,19] is a technique of radiography, particularly adapted for the examining the breasts of the women. It is an essential process for examining and diagnosing the symptoms of breast diseases. There are various kinds of disease symptoms which can include inflammation, skin changes, palpable nodule, discharge, and others. Mammography is intended to detect abnormalities as soon as possible before they cause clinical symptoms [20] The mammography image (Mammogram) is used to detect the breast cancer.

Mammograms provide a detailed anatomy of the breasts. In a mammogram, one can see the opaque radio zones very clearly. The fibro glandular tissue and calcium which are the essential components of the mammary lesions [20] are visualized due to opaque radio zones. Mammography is normally practiced from various dimensions and directions, each of the mammograms is called an incidence. An incidence would be a good candidate to be used for further processing if maximum of the breast tissue can be visualized by a maximum spread on the X-ray plate. Then, distinct implications can be used depending on the breast part to be examined. The profile, face and the oblique external incidences are very commonly used ones. The face and oblique external incidences are called Craniocaudal (CC) and Medio Lateral Oblique (MLO) respectively.

2 Background

In the context of pectoral muscle (PM) segmentation from breast tissues, several studies have been carried out in the literature. For the automatic segmentation of the PM, Guo, et al [21] proposed a study which is based on boundary identification and shape prediction. Their work

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identifies the PM region in MLO view mammograms.

The authors in [13] believe that computer-aided diagnosis (CAD) systems are beneficial for breast cancer detection as it improves the diagnosis accuracy. They have presented some contribution towards the development of a breast CAD system. This work is based on split and merge methodology. Their algorithm used a technique of voting.

Mammography can be utilized for measuring breast density (BD) which is helpful to diagnose breast cancer. For very commonly clinical routines, the radiologists evaluate images using Breast Imaging Reporting and Data System (BIRADS) [22] assessment. Since this method has human intervention and hence has some kind of variability. Therefore, to relieve the burden of medical experts like radiologists and to have a first aid opinion, there is a need to find out some robust and automated approach to measure BD and hence to extract PM which is a challenging task.

Bora, et al. [23] have provided a solution for automatic segmentation of pectoral muscle. They have presented an approach which is based on texture gradient. In another work [25], authors used mammographic images using both CC and MLO views, their work proceeds for segmentation and detection of mammograms in three stages. Ganesan, et al. [28] have made a detailed review on pectoral muscle segmentation. Gubern-Mérida et al. [29] proposed an atlas-based segmentation method for pectoral muscle segmentation to detect breast cancer. In another study [30], the segmentation of the pectoral muscle on a mammogram is based on the study of images using the active contour algorithm.

Also in [19], the authors proposed a method for identifying pectoral muscle in MLO mammography using the linear Hough transformation, this proposal begins with the application of a binarization procedure and the chain code algorithm is used to find an approximate contour of the breast. This contour is used as the input to an active model algorithm. The six points (N1, N2, N3, N4, N5, and N6) forming the contour are represented as follows:

- N1: Pixel at the top left of the upper left corner of the image;
- N5: Lowest pixel on the left edge of the border;
- N3: Mid-point between N1 and N5;
- N2: The most distant point at the limit of N5 in Euclidean distance;
- N4: The point that completes a rectangle with N1, N2, N3 ;
- N6: The most distant point on the border loop from N1.

The region of interest (ROI) of entry is defined by the rectangular region delimited by the zone of points N1, N2, N3 and N4. In some cases, this region may not include the total length of the pectoral muscle but the part presented is sufficient to define a straight line to represent the edge of the pectoral muscle. The proposed method is based on a pretreatment step to highlight the boundary between pectoral muscle and breast tissue and on the gradient of the image along the x-axis (horizontally), and after using the points at the edge of the pectoral muscle to draw a line through the RANSAC linear regression algorithm. In the pretreatment phase, they first set the orientation of the breast in such a way that the pectoral muscle always remains in the upper left corner of the image and then the image is normalized to focus on the intensity of the pixels that fall near the line of the breast skin. The $I'(x, y)$, in Equation (1), represents the image obtained through this process:

$$I'(x, y) = I(x, y) - I_{s(x,y)} - MI_{s(x,y)} < M \qquad (1)$$

where MIs the average value of the inner pixels of the breast tissue, I_s is the smoothed version of the image I. This normalization step produces an image stretch that can amplify the transition amplitude between the muscle and the rest of the breast tissue. For the image smoothing, the authors used a Gaussian filter since it preserves only the large variations in the image that are significant for the detection of the pectoral muscle and then they passed to the calculation of the gradient of the intensity of the image along the horizontal direction using the Prewitt bias which uses a 3*3 kernel, the gradient of the image intensity takes minimum values in the part of the image that surrounds the muscle limit and they have several local minima for each line G_x (i.e. gradient according to x). The obtained results by the proposed methodology provide the points of the pectoral muscle boundary as well as outliers from other regions of the image. As the linear regression is not appropriate because it will be influenced by outliers, they have used the RANSAC approach which produces reasonable results with some probability when more iterations are allowed. Mini-MIAS database was used for testing the overall scheme with 84 MLO mammograms.

There are various other studies on the breast cancer detection based on PM. For the sake of brevity, the reader is referred to Figure 1, it overviews around twenty seven studies from 2004 to 2020. The authors, year of publication and the brief idea of the study are depicted in the figure. The interested reader can dig out further exploration by accessing these contributions.

In this paper, we propose a novel approach to remove PM in MLO observations of mammograms. This approach is based on the ideas of clustering, regions and edges. K-means and Region Growing have been utilized for segmentation of Pectoral Muscle in Mammogram Images. For implementation, experimentation and validation, the proposed technique has been tested on the digital mammography of Mini-MIAS database. Details of the approach are mentioned in the following sections.

Figure 1. A survey of pectoral segmentation methods in the current literature.

3 Methodology

In this work, we propose an automatic approach for segmentation of pectoral muscle in order to have a clear mammogram for the following steps of the computer-aided diagnostic system (CAD).Our proposed technique comprises of two major stages of preprocessing and segmentation. The preprocessing stage helps to get clean images for further processing towards segmentation. The segmentation stage allows the separation of pectoral muscle and the breast tissues. The Mammogram Database used in the implementation and testing in this work is taken from the Mini-MIAS database [31] which contains 322 of the MLO views.

3.1 Preprocessing

The preprocessing step is very important as the mammography images contain a significant quantity of noise, labels, artifacts and digitization lines. This is normally coming from different sources when taking x-ray images .For noise removal, we propose using median filter [32] since it is a nonlinear spatial filter that helps us to remove digitization noises using 3*3 neighborhood windows. This filtering technique allows us to eliminate the noise by keeping the maximum information and without blurring the edges that are very interesting in the step of separation of Pectoral Muscle (PM) and the Breast Tissues. Then, for artifacts and labels suppression, we propose using Mathematical Morphology operators and adaptative global thresholding to extract the Mask enclosing the mammary gland. We use various steps in denoising and removing unnecessary artifacts so much so we achieve a pretreated mammography image. These steps include filtering, thresholding, extracted mask, etc.
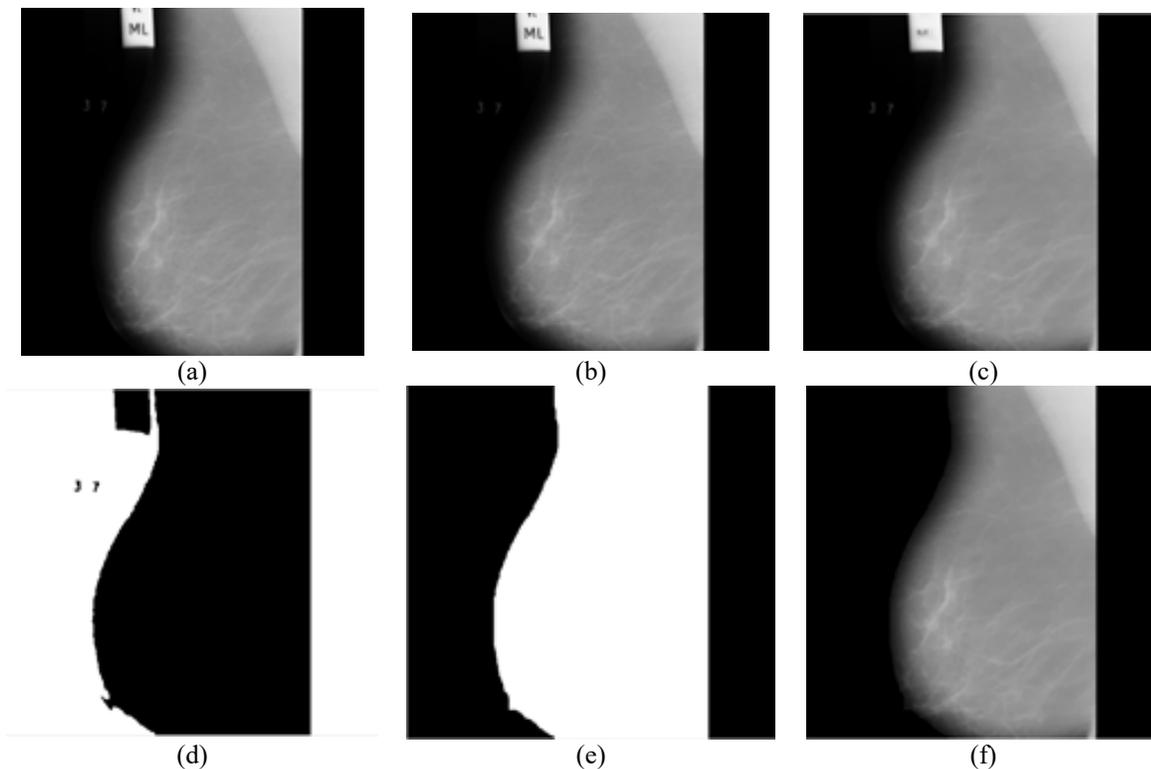
Figure 2. Preprocessing stage for the image mdb006: (a) Original image, (b) Filtered image, (c) Removing Scan Lines, (d) Thresholding, (e) Extracted Mask, (f) Pretreated image.

Figure 2 demonstrates the obtained results, for the database image mdb006, of preprocessing stage passing through different steps. Figure 2(a) presents the original image mdb006, Figure 2(b) is the image after applying the median filter and the salt & pepper noise, Figure 2(c) is obtained after removing scan lines, Figure 2(d) is obtain after thresholding, Figure 2(e) is the extracted mask after removing the isolated pixels that form the labels using Mathematical Morphology operators, and Figure 2(f) is the pretreated image obtained after multiplying the mask.

3.2 Segmentation

Pectoral muscle is a dense region that may affect the process of segmentation and detection of cancerous regions, this is because of the higher intensity of the PM than the surrounding tissues. The existence of PM gives us the false positive results in the steps that consist of the extraction of suspicious zones, so we are obliged to remove it. This motivates to the idea of segmentation and this paper proposes an approach in this regard which is described in

the following sections. This proposed approach of segmentation of PM is based on k-means, Region Growing. These are explained in the following subsections.

3.3 K-means (KM) Algorithm

K-means (KM) [33] is a vector quantization and a kind of clustering algorithm, it is proposed by MacQueen [34] . It is an unsupervised algorithm aiming to separate a set of points into k-clusters by minimizing cluster performance index, error criterion and square error. We orient this algorithm to our work as follows:

1) Choose initial points in order to represent initial clusters (where $x_i \in R_P \in \{1, \ldots, n\}$ are the points to separate).

2) Suppose that μ is a vector of $\mu_k \in R_p$, where μ_k is the center of cluster k, z_{ki} are the indicator variables associated to x_i where:

   $z_{ki} = 1$ if $x_i \in k$;
   $z_{ki} = 0$ else if.

3) Minimize the distortion measure $J(\mu, z)$ according to z and then we associated to x_I the μ_k nearest center.

$$J(\mu, z) = \sum_{1}^{n} \sum_{1}^{n} z_i^k \|x_i - \mu_k\|$$

(2)

4) We calculate the new centers and go back to Step 3 until convergence.

3.4 Region Growing (RG)

The main idea of the seed region growing (RG) algorithm [35] is the agglomeration of pixels with the same properties to construct one region, and each point must have belonged only to one region. To achieve those regions, we should define a criterion that will be true for each area. The region growing technique consists of several steps that are illustrated as follows:

1) We need to define a seed point as a starting pixel for the process of segmentation;
2) Agglomerate all the adjacent pixels that verify the similarity criterion;
3) These new pixels form new seed points to continue the process of segmentation until no more seed pixels satisfy the condition.

We can use area with 3*3 or 5*5 pixels as initial seed points. The criteria or conditions can be defined by different measures like the measure of similarity, mean, variance, etc. At the same time, we can use different conditions in the verification step.
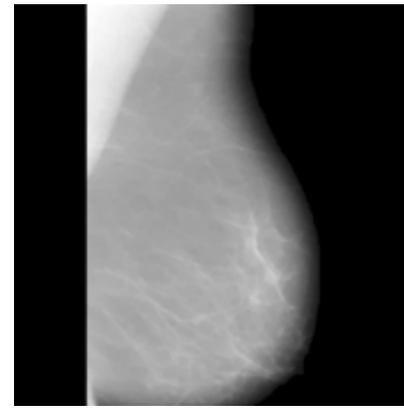
(a)

(b)
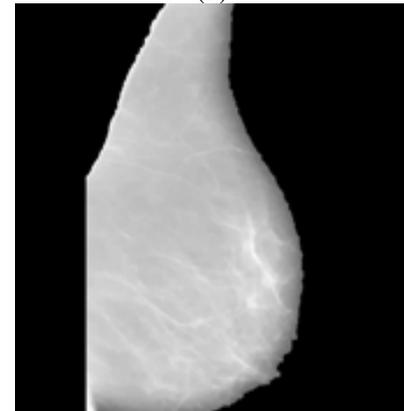
(c)

Figure 3. Orientation of the mammography imagemdb006: (a) Pretreated image, (b) Segmenting image into four clusters using k-means, (c) Removed pectoral muscle using RG.

3.5 Working of the Proposed Approach

K-means allow us to define the clusters that construct a mammary gland using a k value defined above and the reason behind extracting pectoral muscle is the similarity of intensities of the PM and breast tissues. So, the k-means is precise with good performance of the boundaries between areas. Then the region growing algorithm is used to extract the PM without affecting other zones. Before proceeding with the process of segmentation, we determine the orientation of the mammary gland in order to define a seed

point that is effective for all mammography images. We have chosen the left orientation of our images. In order to specify the left orientation of mammograms, we proceed as follows:

1) Divide the images into four blocks;
2) Verify if I (1,128) is black, if it is true, then mirror the image, else nothing to do. Here I is the mammography image in the grey scale levels.Figure 3 demonstrates the steps for the orientation of the mammography imagemdb006 from the dataset Mini-MIAS. Figure 3(a) is the pretreated image, Figure 3(b) shows the segmentation of the image into four clusters using k-means, and Figure 3(c) produces the image when pectoral muscle is removed using RG.

Image	Pretreated Image	PM segmented with KMRG
mdb005		
mdb057		
mdb116		
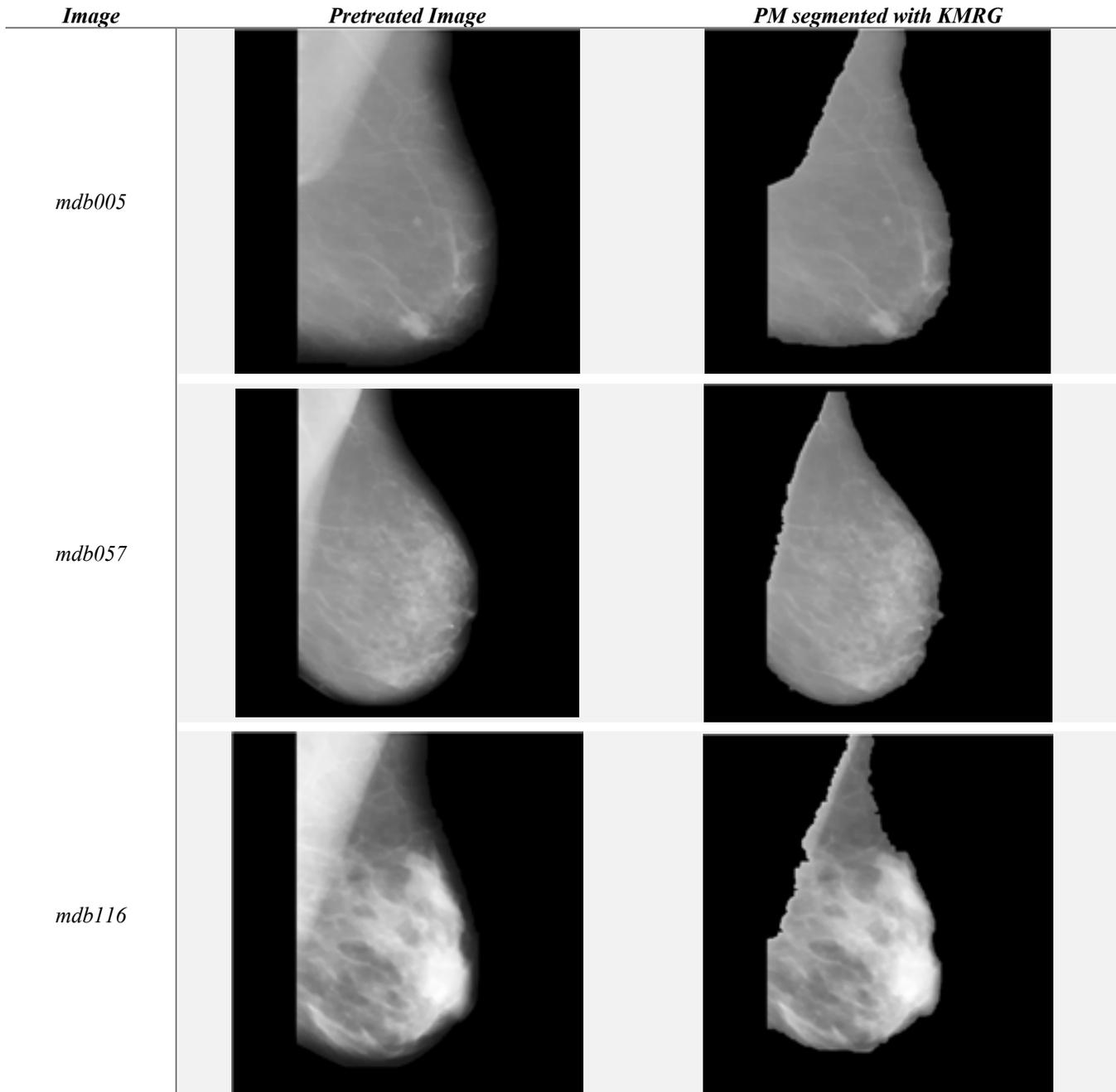
Figure 4. Implementation on images mdb005, mdb057 and mdb116using KMRG.

4 Experiments and Discussion

In this section, the proposed approach KMRG is applied to mammography images. The method is fully automatic for seed region growing, we set an initial point that is adapted to the different data of Mini-MIAS.

4.1 Visual Results

Although, all of Mini-MIAS data set has been tested and experimented fully, but fewer images are shown as sample implementation to demonstrate the visual results. In the first experiment, we chose a set of three mammography images mdb005, mdb057and mdb116 from the database of Mini-MIAS. Figure 4 represents the visual results obtained using the proposed approaches on the three images. The first column (from left) is showing the names of images in Figure 4, the second column represents the pretreated images, third column represents the images after applying the KMRG method, the pectoral muscle is removed in each image.

Image	*Pretreated Image*	*KMRG Method*
mdb182		
mdb266		
mdb303		
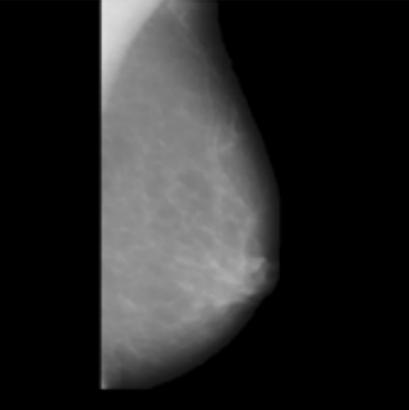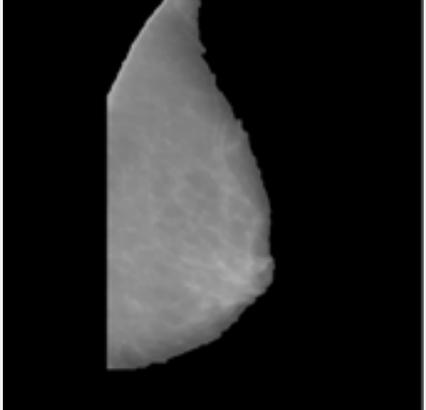
Figure 5. Implementation on images mdb182, mdb266,and mdb303using KMRG.

Let us have another experiment on a different set of images. Figure 5 represents the example for the visual results obtained using the proposed approaches on three different mammography images mdb182, mdb266, and mdb303 from the database of Mini-MIAS. Very similar to Figure 5, middle column is showing the pretreated images. The last column represents the images after applying the KMRG method and pectoral muscle is removed in each image.

4.2 Numerical Results

In the previous section, we saw the effectiveness of KMRG using visual results. To assess the accuracy of the segmentation of the proposed approach, various similarity measures are popular in the current literature. These include DICE coefficient of similarity [16,36,37,38,39,40,41,45] Structural Similarity (SSIM) measure [40,42], peak signal-to-noise ratio (PSNR) [43], mean squared error (MSE) [36, 41], Jaccard similarity index (JSI) [36,16,41], Zijdenbos similarity index [44] and others. For our proposed work, we have chosen DICE and SSIM have to find out the goodness of segmentation between the segmented regions and the ground truth. These are popular measures and are used to determine the perceived quality of digital images.
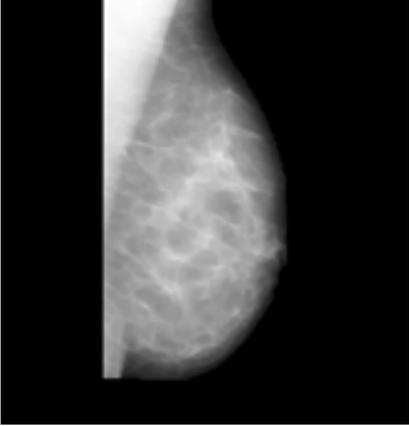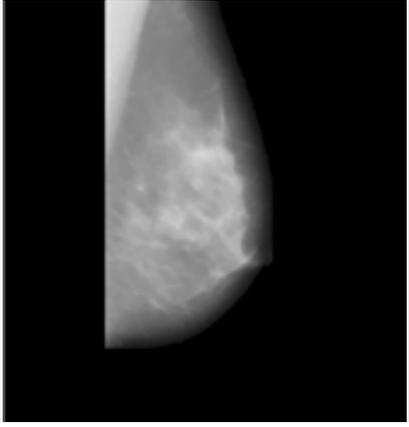
Table 1. The obtained values using DC and SSIM metrics for the approach KMRG.

Experiments	DC	SSIM
mdb005	0.8976	0.8990
mdb057	0.9234	0.9248
mdb116	0.8740	0.9042
mdb182	0.9122	0.9325
mdb266	0.9109	0.9394
mdb303	0.8880	0.9159

Implementations of DICE and SSIM metrics are done successfully for KMRG. If the values of DICE and SSIM are close to 1, it reflects better segmentation accuracy. The Table 1 depicts the results obtained from the metrics of evaluation using the proposed approach of KMRG. These results are also demonstrated, for further clarification, in the graphics made in Figure 6 corresponding to Table 1. One can see that the proposed segmentation method, for both of the similarity measures, shows prominent results on the accuracy of segmentations. However, one can very easily visualize that the segmentation values of SSIM provide better results than those of DICE.
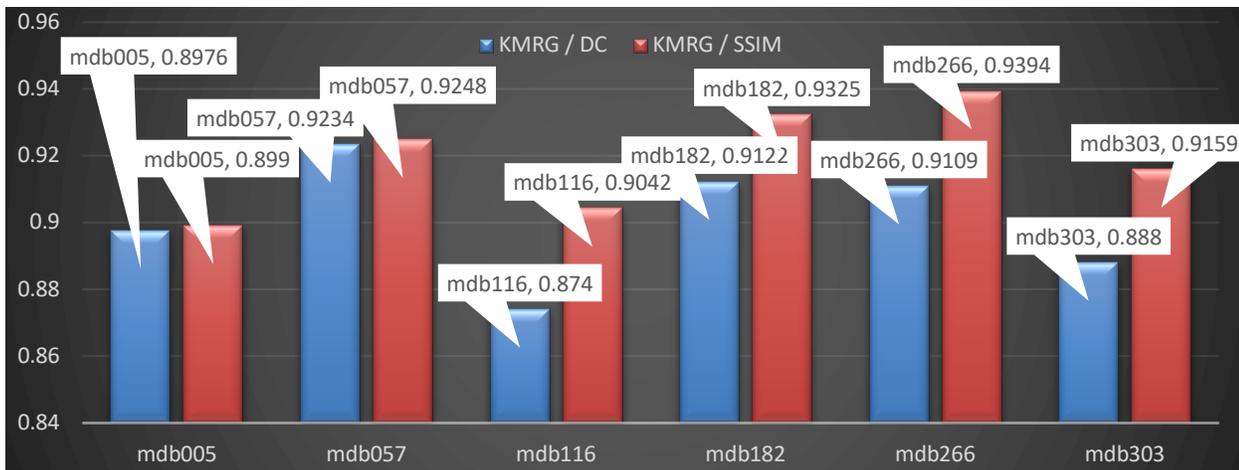
Figure 6. Demonstration of the performance of KMRG method using DC and SSIM metrics.

Figure 7. Visualization of the mean values for Mini-MIAS using DICE and SSIM metrics for KMRG.

Table 2 demonstrates the mean of obtained values for whole Mini-MIAS dataset using DICE and SSIM metrics for the proposed approach of KMRG. Although, all the results obtained are appealing. However, KMRG has experienced best results of 92.47% using SSIM. These results have also been demonstrated in Figure 7 to have a visual feeling.

Table 2. The mean values for Mini-MIAS using DICE and SSIM metrics for KMRG.

Method	% Evaluation	
	DICE	SSIM
KMRG	78.51	92.47

5 Comparative Study

The proposed technique has been compared with various existing techniques including the ones in [1,4,6,7,9,12]. These referred works, from the existing literature, are in the same context as the proposed work. Table 3 draws up a comparison with the proposed approach in such a way that the first column provides the reference paper, second column briefs about the method, third column mentions about the dataset used, and the fourth column throws light on the level of accuracy achieved in the corresponding technique. The proposed technique has proven to be impressive by achieving very high accuracy results. GMEM (92.47% by SSIM with the ground truth) has shown as best as compared to every reported method in Table 3.

Table 3. A detailed comparative study with some existing techniques.

Reference	Main Concepts in Technique	Dataset	Accuracy
Kwok et al., 2004	Morphological information, Pectoral edges by straight line and Cliff detection.	322 MIAS	83.9% of accuracy
Keller et al., 2011	Fuzzy c-means and linear discriminant analysis.	100 MIAS	Correlation of 0.83 and an average JSI of 0.62.
Oliver et al., 2014	Information of position, intensity, and texture is used.	149 MIAS	83% by DICE.
Galdran et al., 2015	Cartoon decomposition into texture and structural components, thresholding, and active contour.	84 MIAS	0.91 by DICE similarity coefficient.
Othman and Ahmad, 2016	Fuzzy c-mean and multi-selection of seeds label.	322 MIAS	Used SSIM, but % is not available.
Pavan et al., 2019	Hough transform and active contour.	322 MIAS	90% by JSI.
Proposed method KMRG	K-means and region growing.	322 MIAS	92.47% by SSIM.

5 Conclusion

A novel technique, namely KMRG, has been proposed for the segmentation of pectoral muscle in mammogram images. It is based on the ideas of k-means and region growing. It detects tumor growth with very high precision and provides automated and effective solution. The proposed technique has been successfully implemented on the dataset of Mini-MIAS. KMRG has been found effective, this was observed both by visual as well as mathematical evaluations using DICE and SSIM measures. It was also found that SSIM provides better results as compared to DICE. A detailed comparative study, with the existing state-of-the-art techniques, has also been made to observe the competitiveness of the proposed technique. It was found that KMRG has shown to be competing using SSIM with the ground truth.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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