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Identifications of Irregularities in Mammographic Images Using Computer Aided Diagnostic Scheme

Dr. S. Karthick[1], Dr. P. Selvan[2]
[1]*Professor, Department of ECE, Erode Sengunthar Engineering College, Erode, Tamilnadu, India.*
[2]*Professor, Department of EEE, Erode Sengunthar Engineering College, Erode, Tamilnadu, India.*

Abstract
Cancer is the leading cause of death among men and women in the world. Breast cancer is the most common cause of death among women among all other cancers. Medical Image Processing is an emerging area, which helps the medical practitioners in diagnosis and surgery planning using appropriate imaging systems. Mammography is a powerful imaging technique used for the early detection of breast cancer. Masses and calcifications are the important features, observed from the mammogram. Mammogram images are considered for this. The region growing approaches, fuzzy c-mean clustering are used to segment the abnormalities from the input images. The results of the proposed image segmentation are compared with each other. The results show that the fuzzy c-mean algorithm techniques give better results than the region growing image segmentation approach.
Keywords: *Medical images, Segmentation, Region Growing algorithm, Breast Cancer, FCM.*

1. INTRODUCTION

Breast cancer is the main significant cause of women's fatality in many countries. Mammography is presently the most effective imaging modality for the discovery of breast cancer and the verdict of the anomalies which can recognize cancerous cells. Surveying studies show that in current breast cancer screenings around 15 to 30 percent of breast cancer cases are missed by radiologists. With the developments in digital image processing methods, it is predicted that radiologists will have chances to decrease this margin of the fault and hence, increase their diagnosis.

In medical image processing, image segmentation is an important research area to get the desired results. Image segmentation is the process in which the original natural image is partitioned into a meaningful region. It helps the radiologists to recognize the affected area of the human body to study the shape and size of cancer. Digital Mammography is the most significant and efficient imaging modality used by radio diagnosis techniques to discover breast cancer. Finding an effective and good accurate method to detect breast cancer remains an uphill task in digital mammography.

2. LITERATURE SURVEY.

Zhao Yu-qian et al (2005) put forward an innovative method to spot out lungs' CT medical image edge with salt and pepper noise. In the work, it is undeniably shown that the algorithm for medical image demising and edge recognition and common morphological such as morphological gradient process and dilation remains edge detectable.

Jawed Nagi et al (2010) proposed the Breast cancer fragmentation technique. It is an automated technique for mammogram identification. Region growing performs disintegration of an image concerning seed points. Elimination of the breast cancer region and the pectoral muscle is an important pre-processing step in the procedure of algorithms. It mainly allows the search for abnormality present in the image of the breast tissue without the unnecessary influence of the surroundings of the mammogram. This approach has been tested using mammogram images of different densities from numerous databases and has shown good results with better precision.

Meenalosini S et al (2012) proposed an innovative technique, in which the segmented mammograms with the aid of region-growing algorithms. In this proposed technique pre-processing was done through a median filter, morphological process, and thresholding techniques.

Bethapudi et al (2013) anticipated an innovative procedure to sense and spot out the mass amounts in digital mammogram images. The method identifies the malignant tissues in three steps: In the primary step, the superfluous background information was removed with the aid of thresholding. The next step is used for the removal of the assistance of the median filter. Subsequently, in the third step, the binary image contours are dragged out. The authors planned to identify the shape of the mass.

3. COMPUTER-AIDED DETECTION SYSTEMS

Computer-aided detection is proposed to be used after the radiologist has finished an assessment of the mammography images and has made an early conclusion whether a patient recall is essential. Since, computer-aided detection is projected as an assistant to digital mammography to reduce search, detection, and interpretation errors, and the radiologist makes the concluding decision if a clinically significant irregularity exists and chooses whether the additional diagnostic assessment is necessary[1]. The anticipation lies in the fact that computer-aided detection systems will increase the sensitivity of digital mammography without considerably aggregate patient recall rates.

3.1 PROBLEM FORMATION

The main objective of computerized breast cancer recognition in digital mammography is to recognize the presence of irregularities such as mass lesions and Microcalcifications clusters (MCCs) in breast tissue[2]. Lesion recognition is possible from a single mammogram image, as is the finding of Microcalcifications clusters, which is exposed to a wide volume of publications.

Whichever way they are spotted, masses and Microcalcifications clusters essential to be classified into their malignant and benign categories[3,4]. The Decent contrast will be accessible in the whole Region of Interest (ROI), both in the pectoral area as well as near the skin line. At first, the mammogram images are improved to highlight some property of the wanted regions (ROIs) through either spatial filtering or time-frequency based approaches. Investigative features are then calculated from the enhanced images (ROIs) and some elementary classification is achieved to discriminate between masses.

The search for irregularities in mammogram images normally uses the breast profile margin to constrain processing on the breast part only, reduce the time processing non-breast areas[5]. To constraint mammogram processing in the breast tissue area only, *mammogram segmentation* is an important step to suppress unimportant areas in mammograms. The main objectives of this paper are,

- To investigate various image processing algorithms, techniques to detect mass lesions in digital mammograms.
- To verify the reliability and accuracy of the developed system using the datasets from different sources.
- To perform a comparative study for identifying the most suitable technique for the identification of benign and malignant abnormalities.

3.2 SEEDED REGION GROWING ALGORITHM

Region growing is the most frequently used region-based technique for image segmentation. Seeded Region Growing (SRG) is based on the traditional region's growing standard of the resemblance of pixels within areas[6,7]. Instead of improving homogeneity parameters as the case with the conventional region growing methods, SRG is operated by selecting many pixels, known as seeds, instead of tuning homogeneity parameters as in the traditional region growing. This type of control allows unskilled and non-expert users to attain decent segmentation outcomes in their earlier effort.

In Seeded Region Growing, segmentation of an image is achieved concerning a set of points, recognized as seed points. Consider many seeds gathered into sets, say, A1, A2,…… An. In some cases, specific sets will consist of single points. Given the seed point, the Seeded Region Growing tries to find a tessellation of the image into smaller regions satisfying the condition that, each connected component of a region meets exactly one of the Ai; limited to this constraint, the areas are selected to be as similar as possible[8]. The Seeded Region Growing process advances inductively from the choice of seed points nominated, namely, the early stage of the sets, A1, A2…. An. In Seeded Region Growing, each step of the process achieves the addition of one pixel to any of the above sets. Then considering the state of the sets A1 after m steps, then all unallocated pixels are calculated with the help of below equation (1),

$$T = \{X \notin \cup_{i=1}^{n}(Ai \mid N(x) \cap \cup_{i=1}^{n} Ai \neq \phi)\} \quad (1)$$

$$\delta(x) = \left|g(x) - mean_{y \epsilon Ai(x)}\ [g(y)]\right| \quad (2)$$

The simplest region mean function is calculated by using equation (2). Where g (x) is the gray level concentration of the image pixel x. If N(x) meets two or more of the Ai, i(x) is taken to be a value of i such that N(x) meets Ai and δ (x) is also diminished[9]. In this condition, it is necessary to classify the pixel x as a boundary pixel and append it to set B, which is a set of already found boundary pixels. This procedure completes step m + 1. This entire process is iteratively repeated until all pixels are allocated. In Seeded Region Growing, the process starts with each Ai being one of the seed point sets. For executing Seeded Region Growing using programming, a data structure named as Sequentially Sorted List (SSL) is used.

A Sequentially Sorted List comprises a linked list of objects, which contains pixel addresses that are ordered according to some feature or attribute[10,11]. At the commencement of each of the steps of Seeded Region Growing, when the algorithm considers a new pixel, the pixel at the beginning of the list is taken out. When adding a pixel to the list, it is placed according to the value of the ordering attribute. In the case of Seeded Region Growing, the Sequentially Sorted List stores the data of T. Which is ordered according to δ (x). It is detected that in executing the Seeded Region Growing procedure, each pixel is visited once only, although, at each visit, each of the 8-connected adjacent pixels is also visited.

Hence, this makes the Seeded Region Growing a speedy process. Achieving a good segmentation performance is dependent on choosing a correct set of seed point as the similarity parameter In maximum cases, if the areas have noise present, single seeds may fall on an outlier, which can result in a poor starting estimation of the region's mean, causing the segmentation to be improper. To avoid this from happening, it is suggested that large seed areas should be used when segmenting noisy areas in images. Furthermore, the area of each seed point should be large enough to ensure that a stable estimation of its region's mean can be found.

3.2 FUZZY C-MEANS (FCM) ALGORITHM

There are two main clustering strategies named as, the hard clustering arrangement and the fuzzy clustering arrangement. The usual hard clustering methods are categorized in all the points of the dataset just too single cluster[11,12]. At this moment, the results are frequently very crunchy, i.e., in image clustering, each pixel of the image belongs just to one cluster. The efficiency of the hard (crunchy) clustering method is reduced in many real circumstances due to some problems like partial spatial resolution, the intensity of overlapping, poor contrast, noise, and intensity inhomogeneities.

The idea of partial membership value was introduced by the Fuzzy set theory and which is explained by a membership function[13]. Due to robust parameters for uncertainty and can retain much more information than hard segmentation methods, the fuzzy c-means (FCM) clustering process was first familiarized by Dunn and later prolonged by Bezdek[14]. The process is an iterative clustering method that produces an optimal partition by minimizing the weighted within-group sum of squared error objective function (Jm) as shown in equation (3).

$$Jm = \sum_{i=1}^{N}\sum_{J=1}^{C} {U_{ij}}^{m} U_{ij} d^2(X_{i,}V_j) \quad (3)$$

Where C is the number of clusters with $2 \leq c < N$, u_{ij} is the degree of membership of x_i in the j^{th} cluster, m is the weighting exponent on each fuzzy membership, v_j is the model of the center of cluster j, d^2 (x_i, v_j) is a distance measure between object xi and cluster center v_j. A solution of the object function J_m can be acquired through an iterative procedure, which is carried out to get the desired segmented output[15].

4. RESULTS AND DISCUSSIONS

4.1 Seeded Region Growing Algorithm

By using the region growing algorithm the breast cancer is detected. The following figures reveal the process of region growing approaches during the operation and it takes additional time to fragment the malignant from the mammographic images.

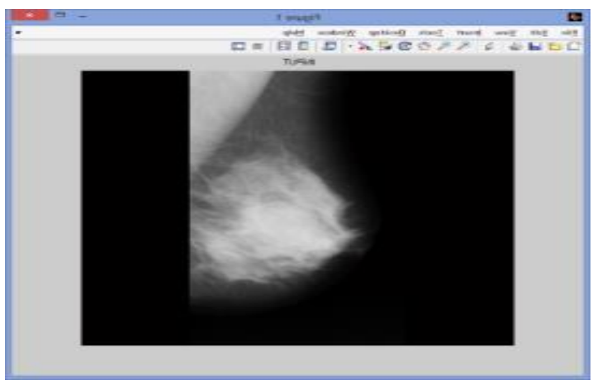

Fig 1. Input Image

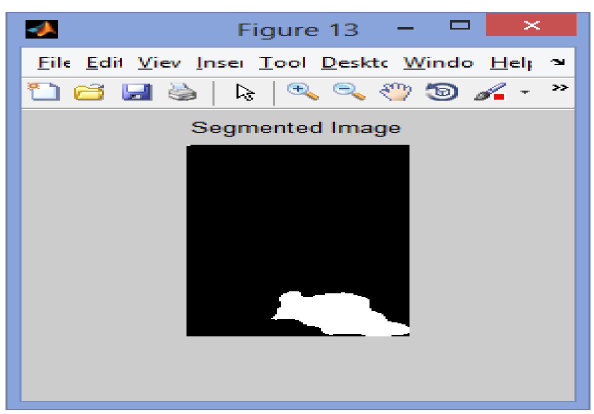

Fig 2. Segmented Image

4.2 Fuzzy C-Means (FCM) Algorithm

The FCM process is best suitable for recasting in matrix theorems. This iterative clustering technique produces the best partition *c* which is obtained by diminishing the weight within the group. The output of the Fuzzy C Means algorithm gives moderate results while comparing with a region growing algorithm.

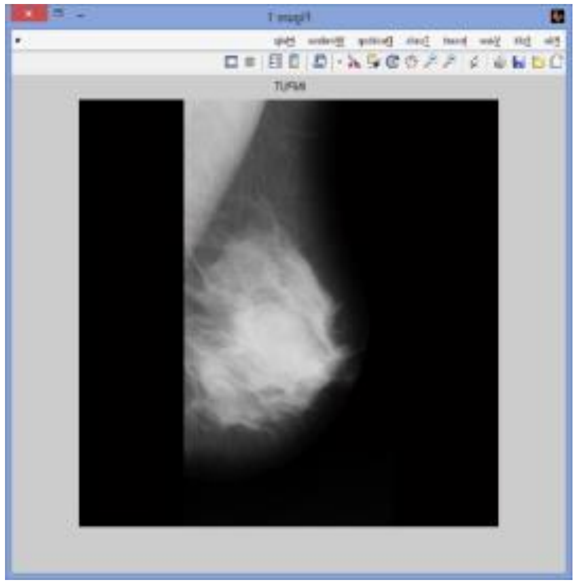

Fig 3. Input Image

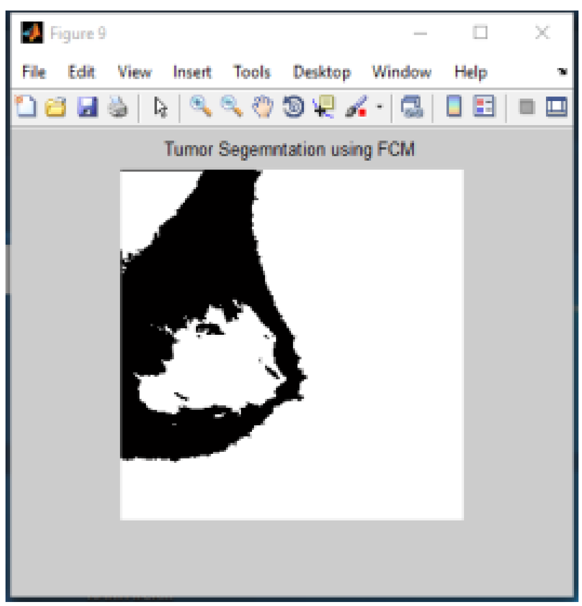

Fig 4. Segmented Image

Below table 1 shows the performance comparison of region growing, morphological and fuzzy c Means algorithm. It shows morphological approaches gives better than region growing and fuzzy C Means algorithmic approaches.

Table 1. Comparison of Table

S.No	Parameters	Region Growing Algorithm	FCM Algorithm
1	Entropy	0.8950	0.7876
2	Standard deviation	35.6871	0.2368
3	Mean	18.4664	0.7644
4	Variance	3.4348e+04	0.1801
5	Co variance	313.4071	0.0051
6	Sensitivity	3.5569	7.6675
7	Specificity	8.8625	7.9877
8	Area (sq.mm)	660	42123
9	Time (sec)	**20.337**	**2.8443**
10	Accuracy	**87.7903 %**	**92.1724 %**

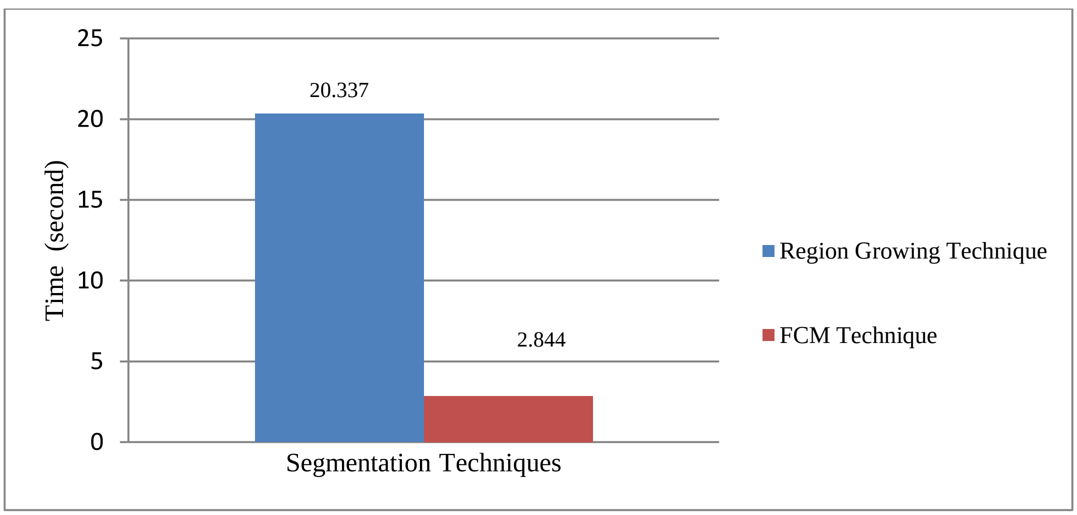

Chart 1. Comparison charts for time consumption

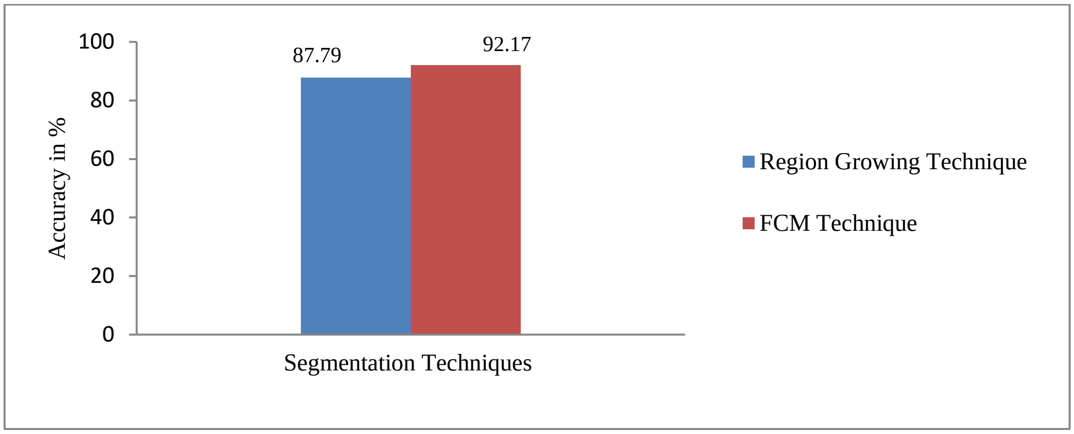

Chart 2. Comparison charts for accuracy

5. CONCLUSION AND FUTURE SCOPE

Discovery an automatic process for breast cancer segmentation is a complicated task. In this research, an innovative morphological image segmentation method, Region growing approach, and Fuzzy C Means algorithm approaches are discussed. In this work, many parameters such as input image, segmented tumor, standard deviation, elapsed time, and accuracy are used to solve the problems. Comparing all these parameters, the morphological approaches gives good results with other methods such as region growing and Fuzzy C Means algorithmic process. The Computer-aided detection approaches for the irregularity finding and grouping in a mammogram is automated. The investigation outcomes obtained demonstrate that the scheme helps the clarification of radiologists in their everyday exercise besides improving their diagnostic presentation. Future work will engage to progress the accuracy and trim down the processing time.

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