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A Comparitive Analysis of Segmentation Techniques in Mammogram Images.

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***Abstract*-Breast cancer became the most dangerous disease that affect the most of the women and which has the less survival rate. Segmentation is the crucial step in analysis of mammogram images. Based on the segmented image further classification is done. Here we compared various available segmentation techniques for segmentation of mammogram images.**

Index Terms—acwe, ddsm, mammogram segmentation, Otsu.

I. Introduction

Mammogram is the effective technique for detection of detection of breast cancer. Early detection of cancer can avoid the risk factors. Masses and micro calcification can be detected by segmentation. Effective segmentation technique can detect this mass efficiently. There are different techniques available for segmentation of mammogram images. In paper [2] various segmentation techniques used for mammogram image proposed .Still the segmentation is not effective. False segmentation of breast tissue as tumour part is also a major problem in segmentation of mammogram image. In this paper we aimed at comparison of available segmentation techniques that lead to effective segmentation.

II. Segmentation

Segmentation is one of the pre processing operations in classification of cancer images. It is the process of separating tumour part from the mammogram image.

III. Thresholding technique

Threshold techniques make decision based on local pixel information and are effective when the intensity levels of the objects fall squarely outside the range of levels in the background. Thresholding is an efficient method to separate objects from the background. Otsu method is optimal for thresholding large objects from the background.

3.1 Otsu Method

Otsu method, is an improved threshold image segmentation algorithm, where the optical threshold should near the cross where the object and the background intersect, the probability of occurrence at the threshold value should divide into two parts. It's one half belongs to object and other half belongs to background. Then apply a new weight to the Otsu method, this weight can make sure that the result threshold value will always reside at the valley of the two peaks or at the bottom rim of a single peak. It ensures that both the variance of the object and the variance of the background keep away from the variance of the whole image. Otsu's method of thresholding gray level images is efficient for separating an image into two classes where two types of fairly distinct classes exist in the image.

3.2 Algorithm

Step I: Compute histogram and probabilities of each intensity level.

Step II: Setup initial ώ (i) and μ (i)

$$\omega_0 = \sum_{i=0}^{t} p_i$$

$$\mu_1(t) = \sum_{i=t+1}^{L-1} ip_i / \omega_1(t)$$

Step III: Step through all possible thresholds maximum intensity

1. Update and ώ(i) and μ(i)
2. Compute σ_{B^2}

$$\sigma_B^2 = \omega_0 \left(\mu_0 - \mu_T \right)^2 + \omega_1 \left(\mu_1 - \mu_T \right)^2$$

Step IV: Desired threshold corresponds to the maximum.

Step V: compute two maxima ώ(i) and μ(i) is the greater max and is the greater or equal maximum.

Step VI:

Desired threshold = $\frac{\text{threshold+threshold}}{2}$

4. Global region based

Region growing based method is based on control growing of some initial pixels called as seed.

4.1 Chanvese method

A Vese Chan and Vese (C-V) model is segmenting an image by detecting different objects boundary. The basic idea of this method is to detect the boundary of the object of interest by starting with a contour around it and moving the contour normally inward until it assumes the required boundary. There are two different kinds of active contour models for image segmentation based on the force evolving the respective contours: 1.edge-based and 2.region-based. Edge-based active contours normally use the gradient information, to find the boundaries of sub-regions and to attract the contours to the detected boundaries. Region-based active contours use the statistical information of image intensity within each sub-region instead of searching for geometrical boundaries.

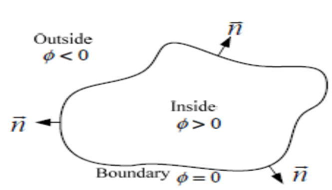

Figure 1. An evolving contour.

4.2 Algorithm

Step I

For an given image I, an initial level set functionφ_0, and parameters μ, v, p, λ1, λ, dt, h.

$$F[\varphi] = \int_{\pi} H(\emptyset) I$$

Where H is the Heaviside function

$$H(x) = \begin{cases} 1, & x. \geq 0 \\ 0, & x = 0 \end{cases}$$

Fitting energy function

$$F(\phi) = \mu\left(\int_{\Omega} |\nabla H(\phi)|\, dx \right)^p + \nu \int_{\Omega} H(\phi) dx$$

$$+ \lambda_1 \int_{\Omega} |I - c_1|^2 H(\phi) dx + \lambda_2 \int_{\Omega} |I - c_2|^2 (1 - H(\phi))\, dx.$$

μ,v.λ1,λ,dt,h and p are parameters selected by the user to fit a particular class of images This is a generalization of the Mumford-Shah functional introduced in [3]

Step II
Set φ= φ(0)

Step III
Compute c1 and c2 for the current φ

$$c1 = \frac{\int_{\omega} I.H(\emptyset) dxdy}{\int_{\omega} H(\emptyset) dxdy}$$

$$c2 = \frac{\int_{\omega} I.(1 - H(\emptyset)) dxdy}{\int_{\omega} (1 - H(\emptyset)) dxdy}$$

Step IV
Update φ using the Chan-Vese iteration
Reinitialize φ to the signed distance function to its zero contours.

V. Level set method

The level set method was first proposed by Osher and Sethian for front propagation, being applied to models of ocean waves and burning flames [4].Then, Malladi applied it for medical imaging purposes [5]. The idea behind the level set method is to imbed a curve within a surface. It can be used to efficiently address the problem of curve and surface. The main idea is to represent the evolving contour using a signed function, where its zero level corresponds to the actual contour. Then, according to the motion equation of the contour, one can derive a similar flow for the implicit surface that when applied to the zero-level will reflect the propagation of the contour.

5.1 ACWE

The segmentation method is based on Active Contours without Edges (ACWE), which was proposed by Tony F. Chan and Luminita. Active contours are curve fitted iteratively to an image. It is based on its shape and image value.

5.2. Algorithm

1. Initialize φ° $by\ \varphi_o$, n=0.

2. Compute c1 $(\varphi)^n$ and c2 $(\varphi)^n$ by

$$(c1(\varphi))^n = \frac{\int_\Omega \mu(x,y)H(\varphi(x,y))\,dx\,dy}{\int_\Omega H(\varphi(x,y))\,dx\,dy}$$

$$(c2(\varphi))^n = \frac{\int_\Omega \mu(x,y)(1-H(\varphi(x,y)))\,dx\,dy}{\int_\Omega (1-H(\varphi(x,y)))\,dx\,dy}$$

3. Solve the PDE in φ from $\frac{\partial\varphi}{\partial t}$= $\delta\varepsilon(\varphi)\left[\mu div\left(\frac{\nabla\varphi}{|\nabla\varphi|}\right) - v - \lambda_1(\mu - c_1)^2 + \lambda_2(\mu - c_2)^2\right] = 0\ in\ (0,\infty)\times \Omega$,

where $\varphi(0,x,y)$=$\varphi_0(x,y) in\ \Omega$,

$\frac{\delta_\varepsilon(\varphi)}{|\nabla\varphi|}\frac{\partial\varphi}{\partial\vec{n}}$ = 0 on $\partial\Omega$ Where $\vec{n}$ is the exterior normal to the boundary $\partial\Omega$ and $\frac{\partial\varphi}{\partial\vec{n}}$ is a normal derivative of φ at the boundary.

4. Reinitialize φ locally to the signed distance function to the curve (optional) check whether the solution is stationary if it is not, then n = n+1 and repeat the algorithm.

6. Morphological Technique

Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test whether it "hits" or intersects the neighbourhood.

6.1 Morphological Filters

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image [25]. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

6.2 Fundamental Operations

The two major operations in the morphological operations are erosion and dilation.The erosion of a binary image f by a structuring element s (denoted f ⊖ s) produces a new binary image g = f ⊖ s with ones in all locations (x, y) of a structuring element's origin at which that structuring element s fits the input image f, i.e. g(x, y) = 1 is s fits f and 0 otherwise, repeating for all pixel coordinates (x,y). The holes and gaps between different regions become larger, and small details are eliminated. The dilation of an image f by a structuring element s (denoted f ⊕ s).produces a new binary image g = f ⊕ s with ones in all locations (x, y) of a structuring element's origin at which that structuring element s hits the input image f, i.e. g(x, y) = 1 if s hits f and 0 otherwise, repeating for all pixel coordinates (x,y). Dilation has the opposite effect to erosion; it adds a layer of pixels to both the inner and outer boundaries of regions.

6.3 Compound Operations

The opening of an image f by a structuring element s (denoted by f ∘ s) is erosion followed by dilation. Opening is so called because it can open up a gap between objects connected by a thin bridge of pixel.

$$f \circ s = (f \ominus s) \oplus s$$

The closing of an image f by a structuring element s (denoted by f • s) is a dilation followed by an erosion. Closing is so called because it can fill holes in the regions while keeping the initial region size

$$f \bullet s = (f \oplus s) \ominus s$$

6.4. Top Hat Operation

The top hat operation is another composite operation. In this the image opened by the structuring element is subtracted from the original image. The brightest spots in the original image are highlighted using this translation.

The top hat operated image when multiplied with the original image gives the segmented image as the output.

7. FUZZY C-MEANS CLUSTERING

In fuzzy clustering, each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the centre of cluster. Any point x has a set of coefficients giving the degree of being in the k th clusterω_k. With fuzzy c-means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster:

$$C_k = \frac{\sum_x \omega_k(x) x}{\sum_x \omega_k(x)}$$

7.1 Algorithm

Step I: Choose the number of clusters.

Step II: Assign randomly to each point coefficients for being in the clusters.

Step III: Repeat until the algorithm has converged (that is, the coefficients' change between two iterations is no more than ε, the given sensitivity threshold)

Step IV: Compute the centroid for each cluster, using the formula (ω_k).

8. Experimental Results

8.1. OTSU Method

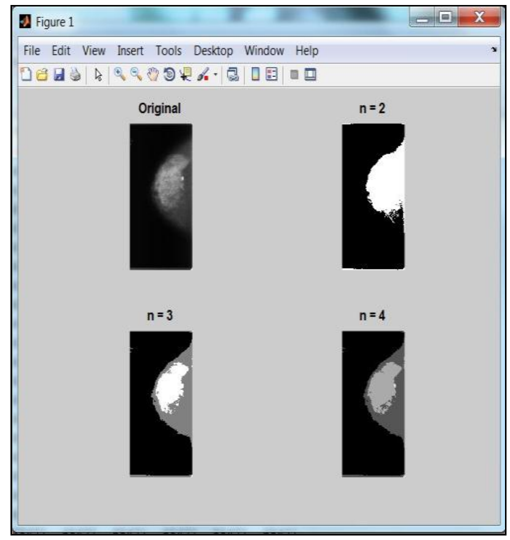

Figure 1: Result of OTSU method.

8.2. Level set

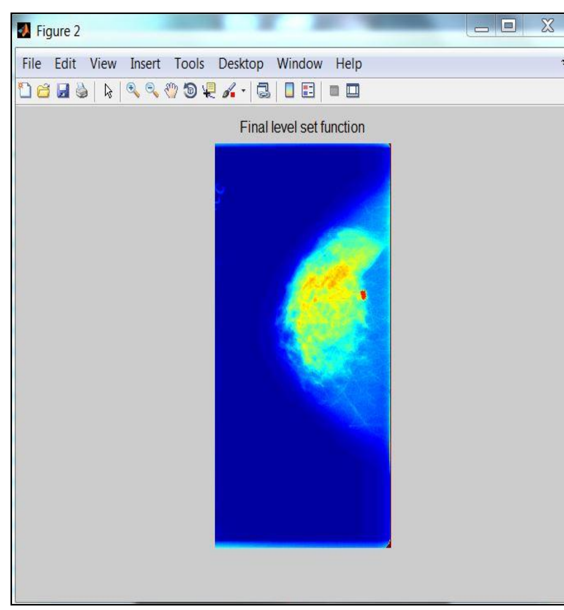

Figure 2: Result of Level set method.

8.3. Regionbased

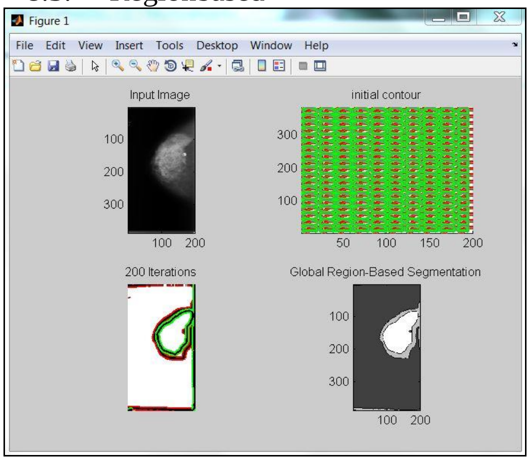

Figure 3: Result of Region based segmentation

8.4. Morphological Operation

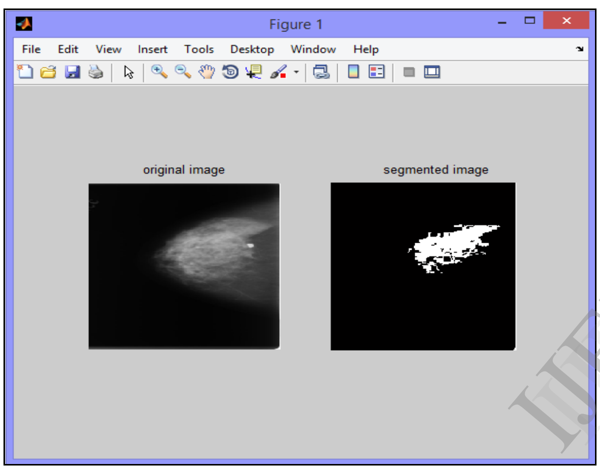

Figure 4: Result of Morphological operation method.

8.5.. Fuzzy C Means

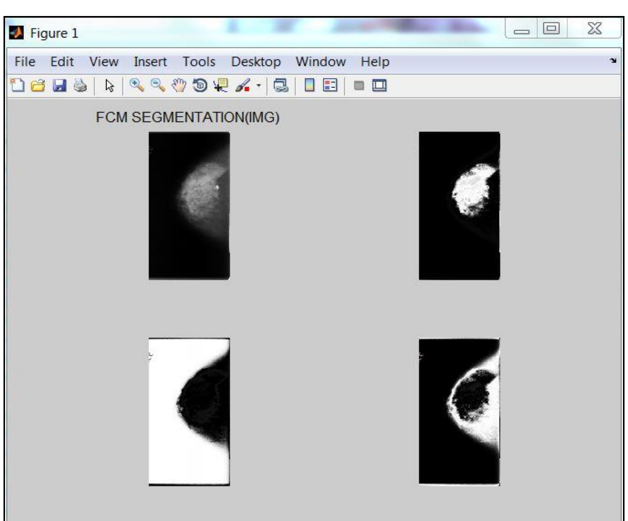

Figure 5 : Result of Fuzzy C Means method.

VIII. RESULT ANALYSIS

METHOD	PSNR	ENTROPY
OTSU	31	1.895
ACWE	29	1.735
MORPHOLOGICAL	21	1.236
REGION BASED	24	1.532
FUZZY C MEANS	26	1.658

Table 1: Accuracy of the above presented methods

It can be observed from above table OTSU method has the highest PSNR rate than others. We have calculated the entropy produced by these methods on applying it for 30 different sets of image from DDSM database

IX. CONCLUSION

In this paper, comparitive analysis of different segmentation methods on mammogram image are performed. Based on the analysis otsu method shows better segmentation result than other methods.It shows accuracy and segmentation of mass area also effective in this method than other three method.

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