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# An Efficient Level Set Mammographic Image Segmentation using Fuzzy C Means Clustering

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ABSTRACT

Breast cancer is the second leading cause of death among women around the world. In this paper, a level set formulation is proposed by using Fuzzy C means clustering for image segmentation. First algorithm, Chan and Vese level set algorithm has the ability to detect and track the arbitrary combination of selected objects or image components in an efficient manner. This level set formulation is established for image segmentation and shape recovery. Second algorithm, Fuzzy C means clustering is utilized to supervise level set initialization and an object indication function. Medical image segmentation is one of the open challenges owing to diversified physiology, pathology, and imaging modalities. Existing level set methods suffer from some inherent drawbacks in face of noise and inhomogeneity. The proposed method is to combine the chan and vese level set method with Fuzzy C means to overcome the initialization, evolution to convergence for image segmentation and also for noise suppression. First, level set algorithm is performed in mammographic image to detect the boundary and remove the noise present in the image. Second, the Fuzzy C means is performed to find the Cluster Center and then combine both fuzzy and level set for reducing initialization problem and encountering weak boundaries and low contrast. MIAS database is used in this work. Thus the cancer region has been segmented in the mammographic image with higher efficiency and accuracy.

Keywords: MIAS database, Level set methods, Chan and vese algorithm, Segmentation and Fuzzy C Means Clustering

## 1. INTRODUCTION

Medical image processing is the most important part of the computer aided diagnosis system and achieves great progress in the past years. Researchers have developed lots of algorithms to solve the problem. According to a lot of uncertainty and inaccuracy of image itself, it is found that fuzzy theory has very good description ability to the uncertainty of the image [4,5] and the image segmentation problem is to classify the image pixels. Fuzzy clustering method is a kind of soft segmentation method and it provides sound result for medical image segmentation. Image segmentation is one of the basic techniques of image processing. Because of the ambiguity of the image, the image segmentation algorithm based on fuzzy clustering gradually get people's attention. Fuzzy C means clustering algorithm (FCM) is one of the most complete and the most commonly used fuzzy clustering method, which uses non-linear programming approach and uses gradient iterative way to get optimal cluster center value [6]. In recent years, some scholars have focused on image segmentation by means of image clustering, the effect of which is better than traditional image segmentation method, but the classical fuzzy clustering segmentation method still has some problems [7-9]. Because the Fuzzy C Means method considers only the gray value information, it is not robust to noise [10]. In section 3 a new image segmentation method based on improved fuzzy c-means is proposed. At last, we give some conclusions.

### *1.1 Literature Survey*

In [1] Jorge D., et al. Proposed a novel model of computer aided diagnosis (CAD) system through breast thermography with the purpose of diagnosing breast cancer. It is based on fuzzy classifier features with a sensitivity of 82.35% and a specificity of 92.15%. A median fuzzy c means approach for detection of masses and macro calcification in mammogram images is proposed in [2]. Segment and detects the boundary of different breast tissue regions in mammograms by using dynamic K-means clustering algorithm and seed based region growing (SBRG) techniques in [3] Elmoufidi., et al. The traditional K- Means algorithm in [4] is incorporated with Ant Colony Optimization and Regularization parameter to segment the lesion portion with maximum boundary preservation.

Various FCM like BCFCM, PFCM, SFCM, FLICM, MDFCM, FCM-S1, FCM-S2, TEFCM, RFCMK, WIPFCM and KWFLICM, has been proposed to overcome the presence of noise and intensity inhomogeneity in MRI images in [5] Samundeewari., et al. A novel level set method for image segmentation in the presence of intensity in homogeneity. The proposed level set method can be directly applied to simultaneous segmentation and bias correction for 3 NS 7T MRI images in [6] choudhry., et al. In [7] zhang, kaihua et al. Proposed an Ant Colony Optimization technique alongside K-Means and Level set to locate the liver region. A new region-based method to properly segment breast and background regions in mammographic images in [8], Li, Bing Nan., et al. These regions are estimated by an Iterative Fuzzy Breast Segmentation method (IFBS).

Based on the Fuzzy C-Means (FCM) algorithm, IFBS method iteratively increases the precision of an initially extracted breast region. In [9] Touil, Asma, et al., proposed A new medical image segmentation pipeline for accurate bone segmentation from computed tomography (CT) imaging is proposed in this paper. A new local Chan–Vese (LCV) model is proposed for image segmentation, which is built based on the techniques of curve evolution, local statistical function and level set method in [10] Pinheiro, et al., In [11] wang, et al., Ant colony optimization algorithm is a fast heuristic optimization algorithm, easily integrates with other methods, and it is robust. ACA FCM can greatly enhance the speed of image segmentation, while reducing the noise on the image. The image segmentation based on ACA FCM is carried out and compared with traditional methods. Experimental results show that ACA FCM can quickly and accurately segment target and it is an effective method of image segmentation. A different clustering algorithm, an artificial immune system (AIS), for data reduction process in [12] Sathish, et al., Detection of edges in an image is a very important step towards understanding image features.

There are large numbers of edge detection operators available, each designed to be sensitive to certain types of edges. The Quality of edge detection can be measured from several criteria objectively in [13]. Aroquiaraj, et al., in [14] proposed is based on the following procedure: Removing the background information, Applying the edge detection technique and retrieving the largest ROI, after getting the close loops, filling is performed in order to highlight the tumor, performing the morphological operations which are erosion and dilation. A novel approach for the detection of breast cancer is used. Many imaging techniques are introduced for the breast cancer diagnosis in [15] proposed. In this ant colony optimization (ACO) based edge detection technique is used for the diagnosing of breast cancer. Fuzzy C-Means is a method of clustering in [16] which allows one piece of data to belong to two or many clusters. This method is frequently used in pattern recognition. It is based on minimizing functions. Fuzzy Partitioning is carried out through an interactive optimization of the objective function, with the update of membership the cluster centers. The variational level set approaches are widely used in image segmentation. To extract the objects from the inhomogeneity image, an improved local and global binary fitting active contours model is presented in [17].

In [18] in this paper, a new local Chan–Vese (LCV) model is proposed for image segmentation, which is built based on the techniques of curve evolution, local statistical function and level set method. The energy functional for the proposed model consists of three terms, i.e., global term, local term and regularization term. In [19] in this paper, presented a novel algorithm for breast ultrasound image segmentation which is based on hybrid of level set and graph cuts. Firstly, speckle reducing anisotropic diffusion. Subsequently, the initial contour is achieved by graph cut. To smooth the boundaries, a boundary item is added into the energy function of level set. At last, the final contour converges to the objective boundary quickly and accurately after finite steps of iteration of level set. In [20] a method for segmenting images that was developed by Chan and Vese. This is a powerful, flexible method that can successfully segment many types of images, including some that would be difficult or impossible to segment with classical thresholding or gradient-based methods.

### *1.2 K Means Clustering*

The existing algorithm Clustering based on k-means is closely related to a number of other clustering and location problems. These include the Euclidean k-medians (or the multisource Weber problem) [11], [12] in which the objective is to minimize the sum of distances to the nearest center and the geometric k-center problem. An asymptotically efficient approximation for the k-means clustering problem has been presented by Matousek [15], but the large constant factors suggest that it is not a good candidate for practical implementation. The K means Clustering function is given by:

$$j(v) = \sum_{i=1}^{c} \sum_{j=1}^{ci} \left( \left\| x_i - v_j \right\| \right)^2 \qquad (1)$$

Where '$||x_i - v_j||$' is the Euclidean distance between $x_i$ and $v_j$. '$c_i$' is the number of data points in $i^{th}$ cluster. '$c$' is the number of cluster centers. K Means Clustering function in eqn (1) shows the distance between the cluster point and the data point. Image is segmented until the iteration stops. This algorithm has some disadvantages such as 1) The learning algorithm requires apriori specification of the number of cluster centers. 2) K Mean Clustering will not work on the overlapping of data. 3) Euclidean distance measures can unequally weight factors. 4) Randomly choosing of the cluster center cannot lead us to the fruitful result. 5) It does not works on noisy data and outliers.9) algorithm fails for nonlinear data set. To overcome the disadvantages of k Means, Fuzzy C Means Clustering is introduced.

## 2. BLOCK DIAGRAM

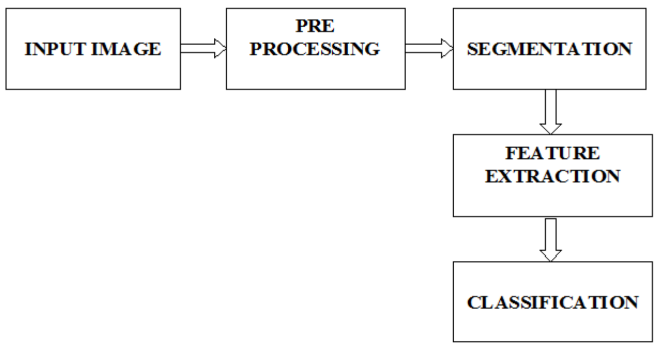


Fig.1.1 Block diagram of Proposed Work

Here the MIAS Dataset is preprocessed using the Level set Method for removing noise and intensity inhomogeneity and then Fuzzy C Means Clustering is performed for segmentation.

## 3. PROPOSED METHOD

### *3.1 Chan and Vese Level set algorithm*

The Level set is performed for tracking and detecting the boundary of an input region. The boundary of the image consist of a closed interface that separates the image into the region inside the boundary and the one outside. LSMs (Level

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Set Methods) express the interface implicitly by embedding it into a higher-dimensional Lipschitz function:

$$\phi(x,y,t)\begin{cases} <0 \; for(x,y)\in\Omega^- \\ =0 \; for(x,y)\in\Phi \\ >0 \; for(x,y)\in\Omega^+ \end{cases} \qquad (2)$$

Where $\Phi$ is an interface separating the image domain $\Omega$, $\Omega^-$ denotes the sub-region inside $\Phi$ and $\Omega^+$ outside. The dynamic level set function $\phi$ with t. Recovering the boundary by checking eqn (2), namely $\phi(x,y,t=T)=0$. Another important advantage of LSMs is that the interface evolution is totally determined by PDEs, where various forces are integrated with the dynamic interface toward.

The level set method is performed in MIAS database for removing of noise, intensity inhomogeneity and ambiguity. The chan and vese level set algorithm is performed as a preprocessing method. The general function for the chan and vese level set algorithm is given by:

$$F^{MS}(u,\Phi)=\mu\cdot Length(\Phi)+\lambda\int|\omega-u|^2\,dxdy+\int_{\Omega/\Phi}|\nabla u|^2\,dxdy, \qquad (3)$$

Where $\mu$ and $\lambda$ are two controlling parameters, and u is a piecewise smooth approximation of the sub-regions. In essence, eqn (3) pursues an optimal interface, either real or virtual, by minimizing a customized cost function of regional homogeneity.

The fitting energy function is decreased in the given image while using the chan and vese level set algorithm, and the minimizing level set function $\phi$ will define the segmentation. In its most general form, the fitting energy is

$$F(\phi)=\mu\left(\int_\Omega\left(|\nabla H(\phi)|dx\right)\right)^p+v\int_\Omega H(\phi)dx+\lambda_1\int_\Omega|I-c_1|^2H(\phi)dx+\lambda_2\int_\Omega|I-C_2|^2(1-H(\phi))dx. \qquad (4)$$

$\mu, v$, $\lambda_1, \lambda_2$ and p are parameters in eqn (4) selected by the user to fit a particular class of images. Note that this is a generalization of the Mumford-Shah functional introduced in [2]; the Mumford-Shah functional is obtained by setting p = 1, $v$ = 0, and $\lambda_1 = \lambda_2 = 1$. Here H is the Heavy side function, I is the image to be segmented, and $\Omega$ is the domain of that image. $c_1$ and $c_2$ are the averages of the image I in the regions where $\phi \geq 0$ and $\phi < 0$, respectively given by,

$$c_1=\frac{\int_\Omega I\cdot H(\phi)dxdy}{\int_\Omega H(\phi)dxdy},\; c_2=\frac{\int_\Omega I\cdot(1-H(\phi))dxdy}{\int_\Omega(1-H(\phi))dxdy} \qquad (5)$$

The required regions in the image can be calculated using eqn (5) in multiple images.

***3.2 Fuzzy C Means Clustering***

After finding the level set of a mammogram image, the Fuzzy C Means Clustering is performed for segmenting the cancer region in the mammography. Fuzzy C Means clustering having cluster center and data points. The euclidean distance is measured in between the cluster center and the data points. The distance should be minimum. The cluster center is randomly assumed. Iteration process is performed until the objection function (J) is less than $\beta$.

***Algorithmic steps for Fuzzy c-means clustering***

Let X = {$x_1$, $x_2$, $x_3$ ..., $x_n$} be the set of data points and u = {$u_1$, $u_2$, $u_3$ ..., $u_c$} be the set of centers.

1) Selecting the cluster center C randomly.

2) Calculate the fuzzy membership '$\mu_{ij}$' using:

$$\mu_{ij}=1\Big/\sum_{k=1}^{c}\left(d_{ij}/d_{ik}\right)^{(2/m-1)}$$

3) Compute the fuzzy centers '$v_j$' using:

$$v_j=\left(\sum_{i=1}^{n}(\mu_{ij})^m x_i\right)\Big/\left(\sum_{i=1}^{n}(\mu_{ij})^m\right),\ \forall j=1,2,\ldots\ldots\ldots c$$

4) Repeat step 2) and 3) until the minimum '$J$' value is achieved or $||v^{(k+1)} - v^{(k)}|| < \beta$. Where, '$k$' is the iteration step. '$\beta$' is the termination criterion between [0, 1]. '$U = (\mu_{ij})_{n*c}$' is the fuzzy membership matrix. '$J$' is the objective function using these steps the segmentation process is carried out in the image. When the objective function is minimum, iteration process is stopped.

**4. SIMULATION AND RESULTS**

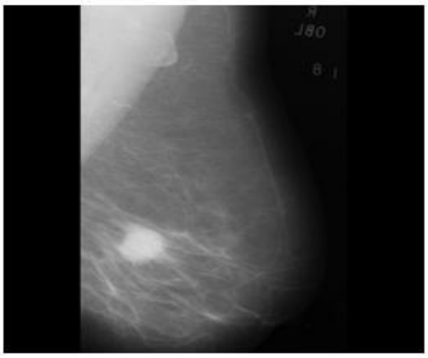

Fig.4.1 Input Image

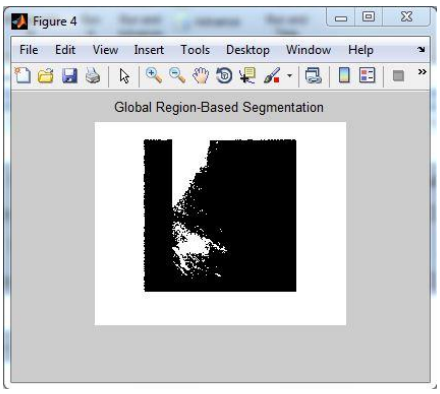


Fig.4.2 Chan and Vese Level Set

Fig: 4.1shows the input image of mammogram. In the MIAS dataset, images are (1024×1024) pixels. Almost 50% of image comprised of the background with a lot of noise. Fig: 4.2 shows, region based segmentation using chan and vese algorithm and it segment the boundary of the breast region.

### *4.1 FCM algorithm output*

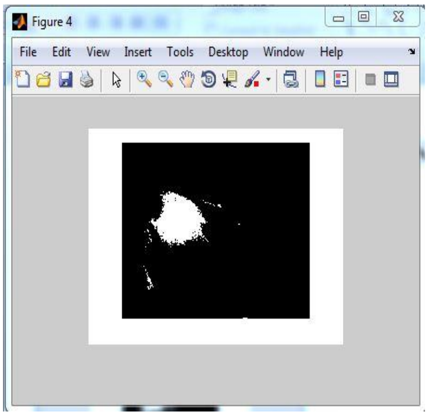


Fig.4.3 Fuzzy C Means Clustering

Fig: 4.3 shows, cancer region is segmented using Fuzzy C Means Clustering

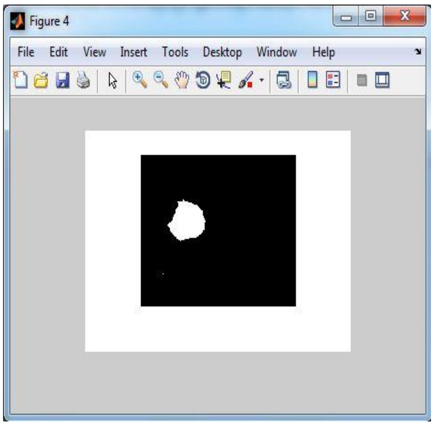


Fig.4.4 FCM Clustering based Level set Output

### *4.2 FCM clustering based level set output*

Fig: 4.4 shows, Segmented Output of Chan and Vese Level set using Fuzzy C Mean Clustering and it is accurately segmented the cancer region present in the Mammogram. Level set method is exactly detect the boundary and Fuzzy C means clustering segment the cancer region accurately.

Table 1 Comparison of Level Set, K Means, Fuzzy C Means and Fuzzy C Means Based Level Set Method

| METHODS | PSNR | RUN TIME | DICE COEFFICIENT |
|---|---|---|---|
| Level set method | 19.522 | 0.0337 | 0.8 |
| K Means | 15.022 | 0.028 | 0.73 |
| Fuzzy C Means clustering | 18.58 | 0.054 | 0.75 |
| FCM based Level set Method | 20.601 | 0.0023 | 0.9 |

Here, FCM based level set method has maximum PSNR value with the maximum dice coefficient. The Dice coefficient could be near to 1. When the PSNR value is maximum then the method has maximum noise resistance. And the run time also minimum in the proposed work.

## 5. CONCLUSION

In this work, the MIAS data base is used as an input. The chan & vese level set algorithm is initially track moving interfaces and spread across various imaging domain. The main benefit of level set approach is that the geometric properties of the contour could be obtained employing a level pair of the surface. It is used to minimize the gradient of the energy. Iterations occur till the energy is minimized and a final segmented image is obtained. FCM can greatly enhance the speed of image segmentation, while reducing the noise on the image. Experimental results show that level set based FCM can quickly and accurately segment target and it is an effective method of image segmentation. Thus the cancer region is segmented accurately because of the maximum dice coefficient and efficiently. In the future work, the segmented region is classify using neural network and feature is extracted from the MIAS data base.

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