# Automatic Brain MRI Image Segmentation using FCM and LSM

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*Abstract* - **The significant objective of this paper is to produce a method that is able to delineate the object of interest or tumor region easily from the available brain MRI images. This is attained by the unification of the fuzzy c-means clustering and level set method. The method proposed performs the segmentation by smoothly exploiting the spatial function during FCM clustering. Since, we are utilizing the FCM which could prove the automaticity of the method by dividing the original image into clusters and then using one cluster for automatic initialization. This in turn helps in making the whole processing less tedious with reducing the time as well. Thereby, if considered it could be competent tool in future. Secondly, to find the contour of tumor region in the original image the proposed method uses the level set method which comes in handy in situations where the topologies of the images changes frequently by merging or splitting in two. Also, the proposed methodology makes use of variational level method in place of generic level set method which in turn eliminates one more flaw of re- initializing the contour during segmentation. When we are using the segmentation methods which are manual then it can lead to a situation where different medical experts generate different results which can also overcome by using the proposed approach.**

***Keywords - Image segmentation, level set methods, Fuzzy c-means, defuzzification, variational level sets.***

## I. INTRODUCTION

Image segmentation is such a process that works by segregating any arbitrary image into non-intersecting regions. The regions obtained after this division should be such that each region is homogenous and the union of any two adjacent regions is heterogeneous. In this paper, the segmentation is performed on medical images especially brain MRI images however, the proposed algorithm can be significantly used in general segmentations as well. The segmented images in the field of medical imaging are used to examine the anatomical structures and also in diagnosis and assisting in surgical planning. There are several neurological circumstances that amend the volume, shape and distribution of brain tissue, therefore, MRI is the favored imaging modality [1]. This elemental technique of image processing is an important component of image analysis and vision system. Several practical applications involve the extraction of exact location of tumors in medical imaging and other pathologies. Also the location of various objects like roads, forests etc. in satellite images are readily possible. Segmentation is one of the most crucial and imperative task in the computerized image analysis process. Thus, the image segmentation technique [14] chosen should be accurate in order to successfully implement the consecutive steps.

Fuzzy set theory has become progressively enticing amidst several image segmentation techniques available due to its robustness for uncertainty and can possess information with much more accuracy and simplicity than other techniques of segmentation. Since FCM after its introduction in 1965 by LotfiZadeh has some weaknesses and several attempts [2] like using the objective function FCM, using the neighbor pixel in addition to the pixel and even pixel division has been done. FCM clustering is well known as an unsupervised technique for cluster analysis in which the data points are allocated to clusters in a fuzzy sense, as in fuzzy logic, rather than belonging to one cluster.

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The primitive active contour model designed by Kass *et al.* [3] extract the objects from an image by moving the explicit parametric curve yet it hold on to some drawbacks such as trouble in handling topological changes [4] and its need of parameterization. The elemental purpose is to express the contours as the zero level set of an implicit function which is defined in a higher dimension, commonly cited as level set function which further is emerged according to partial differential equation (PDE) as categorized by level set method (LSM). Thus, the approach entertains a variety of advantages such as automatically handling the topological changes [9] and allows the level set function to retain its function on a fixed grid. Earlier this PDE needs to be converted to an evolution PDE of parameterized curve using Eulerian formulation; hence, an alternative is adopted. By minimizing an energy function defined on the level set function, the evolution PDE can be derived more conveniently and are usually [10] referred as variational level set methods.

The objective of this research is to suggest a new technique for MRI brain segmentation using integrated level set method and fuzzy c-means (FCM). Fuzzy c-means is been applied so that the procedure can process the segmentation of images automatically. The main advantage of automating the process is that it has made the processing much less tedious and not at all time consuming.

## II. PERTINENT WORK

### *A. Fuzzy c-means clustering*

Fuzzy sets are usually referred as expansions of classical sets. Unlike classical sets, a fuzzy set permits partial membership. An arbitrary element p can belong to different fuzzy sets with different degrees of membership. This provides a much more reliable approach to solve problems intrinsically affected by uncertainty. Firstly [11], by using fuzzy membership for each group, the FCM algorithm authorize pixels. We have assumed P = (p1, p2,., pN), which represents an image possessing N pixels to be divided into c clusters, where $p_i$ denotes multispectral data. The algorithm [5] explained is an iterative escalation that reduces the cost function and is defined as shown below:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^{m} \, ||p_j - v_i||^2 \qquad (1)$$

where $v_i$ is the ith cluster center, $u_{ij}$ means the membership of pixel $p_j$ in the $i^{th}$ cluster, m is a constant, and ‖.‖ is a norm metric. The attribute m is responsible for controlling the fuzziness of the resulting partition.

Since in an image the neighborhood pixels are highly correlated i.e. they share similar feature values and probability to belong to the same cluster which is an important characteristic in spatial clustering. This spatial relationship can help in improving segmentation results. To escapade the spatial data, a spatial function is defined and is shown below,

$$h_{ij} = \sum_{k \epsilon NB(p_j)} uik \qquad (2)$$

where $NB(p_j)$ represents a square window centered on pixel $p_j$ in the spatial domain. The spatial functions consolidate the original membership thereby maintaining unchanged clustering result in a homogenous region and for a noisy pixel; the function with the help of its neighboring pixels weakens weighting of noisy cluster which is a rectification of misclassification of pixels from noisy regions. Then, each pixel is assigned the specific cluster according to its maximal membership and is known as defuzzification [1].

Defuzzification is such a process that significantly produces a perceptible outcome in fuzzy logic, [12] given analogous membership intensity of the fuzzy sets utilized. It is mostly needed in fuzzy control systems. These eventually possess some varied rules that further produces a fuzzy result by mutating a number of variables, which means that the result in fuzzy sets the membership functions illustrate the results. The simplest but rarely used defuzzification method is to select the set acquiring maximum membership value.

A commonly used defuzzification technique is *center of gravity*. Firstly, we have to add together the results of the rules in an appropriate way. The graph of a triangle can be called the most common fuzzy set membership function. Now, if the triangle in the graph needs to be cut someplace between the top and bottom in a straight line and consecutively the removal of the top portion is also done, then eventually a trapezoid is formed by the remaining portion. Afterwards [13], all of the trapezoids obtained are overlapped one upon the other, so that a sole geometric shape is achieved. Then, the *fuzzy centroid,* which is the centroid of this shape, is calculated and the *x* coordinate of this fuzzy centroid is referred as the defuzzified value.

### *B. Variational level set method*

While executing the generic level set methods it is an indispensable requirement to maintain the growing level set function contiguous to the signed distance function [6] so that it can be prevented from getting too steep or flat near the surface. The broadly used numerical strategy to maintain the interface evolution stable and to ensure usable results, a process known as re-initialization is utilized. Nevertheless, re-initializing produces several conflicts between the theory and implementation of level sets as it leads to some abominable effects such as shifting the zero level set away from its original location. The problem of how and when to apply re-initialization has now become an issue.

There are several impressive ideas by which we can implement re-initialization. Fast marching method proposed by Sethian [9] solves the Eikonal equation on both sides of the interface thereby, readily calculating the signed distance function. Fast sweeping method [8] is another convenient method for solving this equation.

However, a new variational formulation proposed by Chunming Li [7], which suggests the adjoining of the signed distance function by pushing the level set function thereby entirely eliminating the usually practiced re-initialization process which is much costly nowadays. An internal energy term and an external energy term are subsequently encompassed by the variational energy functional. The aberration of the level set function against a signed distance function is condemned by the internal energy term, while the movement of the zero level set to the desired image features is commuted by the external energy term. Therefore, the progression of the corresponding level set function is the overall energy functional that is minimized by the gradient flow during the evolution due to internal energy which is commonly kept as a close signed distance function automatically. Variational level set methods involves the use of continuous gradient descent method to minimize energy functional over a space of level set functions for image segmentation of arbitrary images. The internal energy i.e. curve length is included in the functional for regularization while the external energy is used for aligning the curves with object boundaries.

*Variational level set formulation without re-initialization considering penalizing energy*

As explained by Chunming Li, we can originate the generic interface evolution problem considering the constraint on signed distance i.e. Eikonal equation, as the given constrained minimization problem,

$$\min_{\phi} \ \square(\phi) \text{ subject to } |\nabla\phi| = 1 \tag{3}$$

Thus, to avoid re-initialization a penalization term is introduced as shown below,

$$P(\phi) = \lambda \int_{\Omega} 1/2(|\nabla\phi| - 1)^2 \, dxdy \tag{4}$$

The following integral will help in characterizing how close a function $\phi$ is to the signed distance function in $\Omega \subset R^2$ .Using $P(\phi)$, we introduce the following variational formulation,

$$\varepsilon(\phi) = \mu P(\phi) + \varepsilon_m(\phi) \tag{5}$$

where $\mu$ is the attribute managing the overall effect of penalizing the deflection of $\phi$ from the signed distance and $\varepsilon_m(\phi)$ is the energy that will help in driving the motion of zero level curve of $\phi$. In this paper, the gradient flow that will minimize the functional $\varepsilon$ is given below, also known as Gateaux derivative [7],

$$\frac{\partial\phi}{\partial t} = - \frac{\partial\varepsilon}{\partial\phi} \tag{6}$$

Since $\varepsilon_m$ depends on image data thus, referred as external energy while $P(\phi)$ wholly depends on $\phi$ therefore, known as internal energy.

Also, the affect of the value of standard deviation on the result of the final contour can be adverse. The Gaussian distribution of the input image plays quiet an important role as the edge-indicator solely depends on it. The values of Gaussian function and the standard deviation are directly proportional to each other. The large proportion of statistical analysis is based on the Gaussian distribution. Its main feature of averaging almost always guides to a bell-shaped distribution which is sometimes known as normal distribution. In Gaussian distribution, the width of the bell is shown by the standard deviation. Narrow bell and high peak are observed in small standard deviation while a wide bell and low peak is given by the large standard deviation. The variational level set method is tested on various types of medical images such as X-ray image, MRI (Magnetic Resonance Imaging) [11] image and ultrasound image. The sharp corners and cusps of the brain tissue are easily handled, and the topology change of the brain boundary is also managed by the variational level sets.

## III. PROPOSED METHOD

In this paper, we have proposed such an integrated method which primarily combines fuzzy c-means and level set method without re-initialization to yield efficient results. The main steps involved in the proposed method include the integration of fuzzy c-means and level set method algorithm can be explained as follows:

1. Read the input image.
2. Apply the fuzzy c-means to divide into clusters.
3. Choose the fuzzy cluster to define initial contour for modified level set method.
4. Use the above contour in input image in level set method to obtain the desired image segmentation.
5. Display the segmented image.

The flow chart of proposed algorithm can be shown as follows:

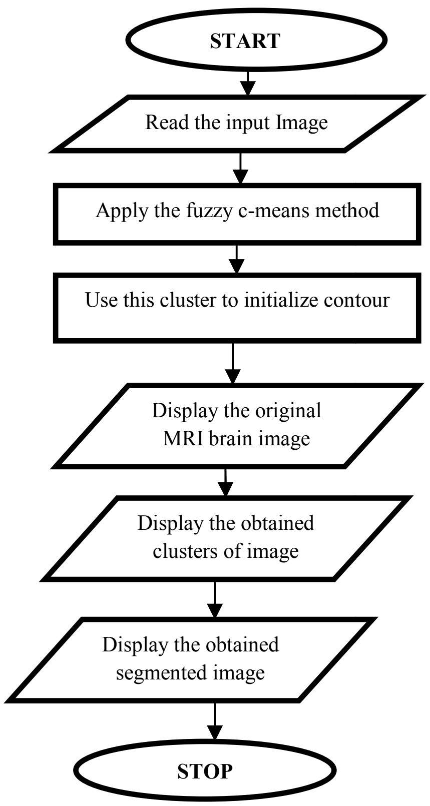


*Fig .1. Proposed Approach*

## IV. EXPERIMENTAL RESULTS

The tumor region is the area of interest that needs to be segmented out. The variational level sets algorithm is implemented while testing the MRI brain images in the segmentation program. We achieve the boundary of the object or region of interest by evolving the level set curve towards the target region. The contour evolved successfully from a circular shape to the arbitrary shape which is the tumor region in our case. This indicates the contour manage to evolve well as the final contour resembles the exact shape of tumor in brain. The experiments were conducted on different medical images. Matlab R2010a (Mathworks)in Windows 7 was used to implement both the fuzzy c-means and level set method algorithm. All experiments were performed on Dell Intel core i5 processor (2.40 GHz) and 4.00 GB RAM. The results are shown below,

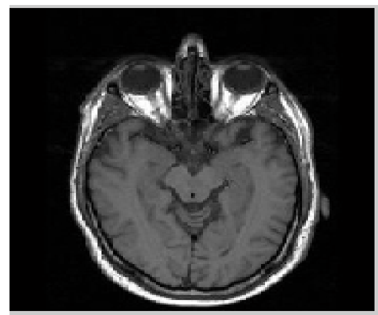

*Fig.2.Brain Transversal T1 image (Original)*

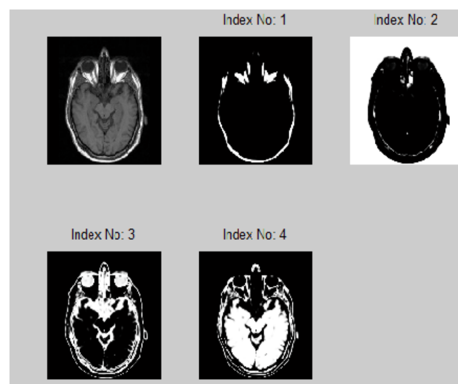


*Fig .3. Clusters obtained after applying fuzzy c-mean*

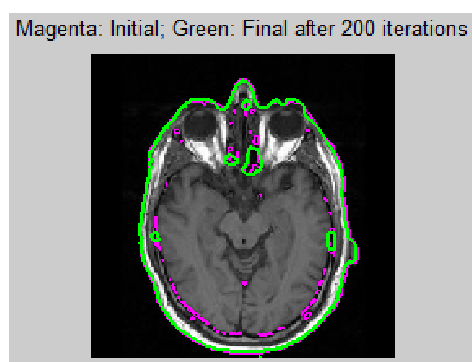


*Fig .4. Segmented image after 200 iterations*

In Fig.2, we used brain MRI transversal T1 image as an input for the Matlab implementation of our proposed algorithm. Fig.3, shows the results of fuzzy c-mean clustering technique, that is, the number of clusters formed after the fuzzy clustering procedure. And finally the Fig.4 depicts the results of proposed method for a 350 × 350 pixel of brain MRI transversal T1 image. It took total 35.6480 seconds to obtain the segmented image with 200 iterations.

We have performed the same segmentation procedure on another image and verified whether it can locate the presence of tumor in that case. The results are shown below,

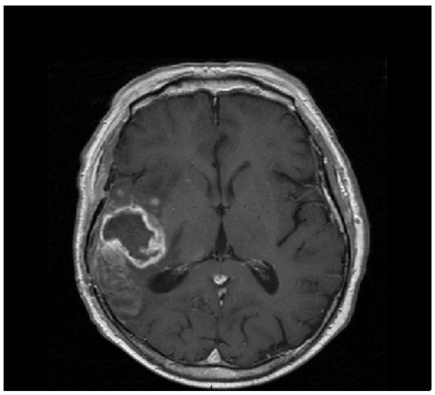

*Fig.5. Original Brain MRI image*

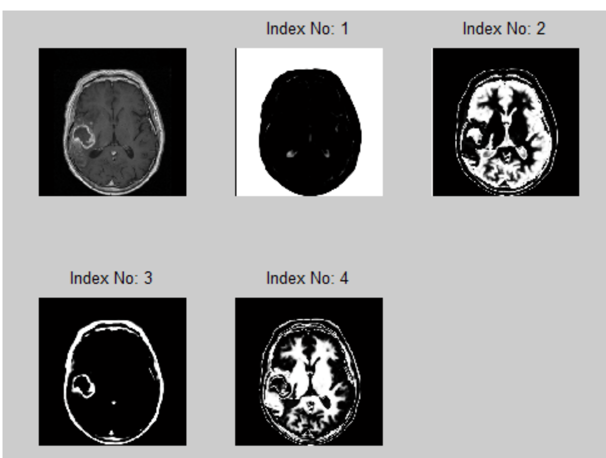


*Fig.6. Clusters obtained after applying FCM*

The final resulting image is obtained after 0.20532 seconds and it clearly shows the exact location of tumor region in the brain MRI image. One important point to note is that both the images are immune to the presence of noise since we have applied the Fuzzy c- means clustering which has made the image smooth. Therefore, there is no effect of noise on the image which is going to be segmented.

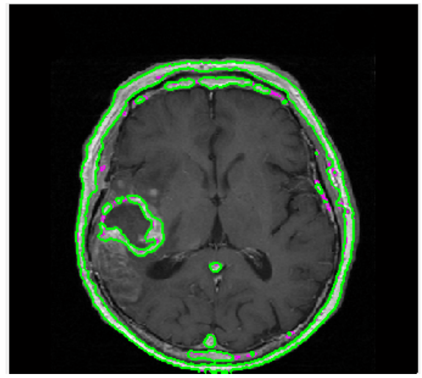

*Fig.7. Segmented image after 100 iterations*

## V. CONCLUSIONS

In this project for medical image segmentation the level set methodology has been proposed. Since, the variational formulation is used which consists of two energies, internal energy which chastises the deflection of the level set function against a signed distance function and to move the zero level set towards the required feature it uses the external energy. This variational level set procreation has three major benefits. First, to speed up the curve evolution a larger time step is used. Second, the elimination of re-initializing has helped in reducing the processing time. Third, for the objects of different shapes the level set curve can be easily implemented.

The above discussed algorithm when processed shows the utility of our proposed method in segmenting the MRI image particularly with weak object boundaries, which is very difficult for fuzzy c-means and level set method to apply. In this paper, our proposed algorithm entirely eliminates the need of manually initializing the contour for level set method. Our proposed method demonstrates relatively good performance for objects with weak boundaries specially when dealing with MRI images. Since the method proposed is automatic therefore it is quick and relatively free from errors as well.

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