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Analysis of Brain Tumor Using Fuzzy - Clustering Level Set Method.

KEYWORDS: MRI, Level Set Method, Fuzzy – Clustering

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ABSTRACT *This paper presents an improved level set method integrated with fuzzy clustering for brain tumor segmentation. Individually, fuzzy logic lead to time consuming process and level set method required manual intervention for calculation of active contour area. A new level set algorithm is applied on brain MR images for tumor detection. This process is more robust as compare to other individual methods. In this process we reduce number of operations per iterations and improves the efficiency. Performance evaluation has been done on various MR images. The result confirms its effectiveness for brain tumor detection.*

1. Introduction

Magnetic resonance imaging (MRI) can provide images with excellent spatial resolution and superb soft tissue contrast. The anatomical and functional information's are derived from these images. It is important to accurately segment MRIs for data analyses. MR image segmentation is very challenging task due to weak contrast and poor resolution. During the last two decades, variational and partial differential equation-based methods for image segmentation and brain tumor analysis have become quite popular [1]. Active contours have been the most influential variational method for image segmentation, which are curves defined within an image domain that can conform to an object boundary within an image under the control of internal forces and external forces [2, 3].

In active, the basic idea is to evolve a curve around the object to be detected and the curve moves toward its interior normal and stops on the true boundary of the object based on the minimization energy. The active contour method can be classified as the snake and level set methods proposed by Osher and Sethian [4, 5]. Snake is a semi-automatic method based on an energy minimizing spline guided by the external constraint forces and pulled by image forces toward the contours of the targets. The main drawbacks of the snake method are its sensitivity to the initial conditions and the difficulties associated with the topological changes for the merging and splitting of the evolving curve. The level set method has become popular because it can handle the complex geometries and topological changes. The level set is in fact a shape driven method, which uses a properly defined speed function and can grow or shrink to take the shape of any complex object of interest. The level set method does not depend on the parameterization of the surface [6]. This makes it quite flexible in shape modeling and image segmentation. In the level set method, the initial contour can be anywhere with an arbitrary size and the position of the initial contour does not affect the final result. On the other hand, there are difficulties in using level sets that makes them less useful in some circumstances. One problem is that the level set formulation entails the tuning of several parameters. In some methods reported in references [7-9], the interactive rates for solving the level set partial differential equation give the user immediate feedback on the parameters and controls the shape of the level set in real time. On the other hand, the main shortcomings of such methods are that they increase the user interactions and provide better segmentation results if the user is familiar with the level set method and region of interest. Leventon et al. [10] provided an automatic and more generic method for the segmentation of tumors through a combination of level set evolution with the statistical shape constraints. The main drawback of this method is that it may be difficult to obtain prior statistical knowledge in many cases, particularly for tumor segmentation.

A new region based method is proposed for boundary detection. This method can detect all contours without knowledge of initial condition, which makes it efficient for future use and overcome the drawback of boundary leakage. The major difficulty faced by level set method is its requirement of different parameters. It requires calculation of parameter value manually at each level. This makes this method very time consuming and tedious to apply on different brain images. To overcome this major drawback of level set method, a new fuzzy level set algorithm is proposed for calculation of tumor area in MR images. New fuzzy clustering introduces spatial information during an adaptive optimization that eliminates the intermediate morphological operations, fuzzy clustering is used for calculation of controlling parameters in level set method and a new fuzzy level set algorithm is defined for tumor detection which is different from other algorithm [10, 13, 14].

2. Fuzzy clustering

Fuzzy c-mean (FCM) and fuzzy k-means are most popular methods of fuzzy clustering for medical image segmentation. The FCM algorithm derived from fuzzy k-means algorithm. In detail, k-means algorithm needs to assign N objects into K clusters (K<N) whereas N is Nx*Ny number of pixels in an medical image. The desired results required centroid of each cluster and N objects value. In k-means clustering each object is limited to one and only one K clusters [11, 12, 13].

3. Level set function

Level set uses variational boundaries for brain image segmentation [14, 5]. Segmentation of images by means of active contours is well known approach [3,15,16]. Level set method utilizes parametric characteristics of active contour which require PDE's and approximate active contour by

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tracking zero level set $\Gamma(t)$

$$\emptyset(t,x,y) < 0 \; (x,y) \text{ is inside } \Gamma(t) \qquad 1$$
$$\emptyset(t,x,y) > 0 \; (x,y) \text{ is outside } \Gamma(t) \qquad 2$$
$$\emptyset(t,x,y) = 0 \; (x,y) \text{ is at } \Gamma(t) \qquad 3$$

The implicit interface Γ may be comprised of a single or series of zero iso-contours.

4. Proposed Methodology

Both fuzzy and level set methods are integrated to overcome the drawbacks of individual method and find out more accurate results. The proposed algorithm of Fuzzy c-means level set method is defined in following steps:

I. Enhancement

It is very much essential to enhance the quality of MR images to improve the interpretability or perception of information in images for human viewers, or to provide better input for other automated image processing techniques so that accurate results can be obtained. Here,we use the following enhancement techniques.

A) Contrast Improvement

Here the intensity values in grayscale input image are mapped to new values such that 1% of data is saturated at low and high intensities of input image. This increases the contrast of the output image. The linear mapping of intensity values with y as 1 is used for the purpose. y here refers to weight used for mapping intensity values of input to output image. In addition to y, this mapping also depends on four threshold values that are higher and lower thresholds for input as well as for output. The threshold values must be between 0 and 1. The technique maps the intensity values in input image I to new intensity values in output image J such that the values between lower and higher threshold of input should be mapped to values between lower and higher threshold of output [17]. Intensity values below lower and above higher threshold of input are clipped; that is, values below lower threshold of input map to lower threshold of output, and those above higher threshold of input map to higher threshold of output. The mapping is done as given by (3). Here since the mapping is for 256 (0-255) intensity values we pre-calculate the mapping so that each of the threads need not spend its time in calculating it again. This speeds up much of the time also instead of calculating it for each and every pixel of image we calculate the new intensity value for each of the 256 intensity values and then map it to each of the pixels of the image.

B) Mid-range stretch

This enhancement technique stretches the middle range intensity values and thus highlights or improves the quality of brain tissues and lightens the non-brain tissues present in the MRI image. Since here there is need to segment out the brain tissues, the mid-range stretch techniques yield good results. It takes into consideration the intensity values of brain and non-brain tissues. The intensity values of brain tissues lie in the range of 0.2-0.7 as per literature survey. In order to apply mid- range stretch to an image we need to map each and every pixel of the grayscale image to a value between O to I just by dividing the intensity value by 255 as shown in (4)

$$X_{ij} = Image\ I/255 \qquad 4$$

Where, i and j corresponds to row and column index of the image matrix respectively. Then we need to compute a function f(x) on the X matrix obtained from (4). The function f(x) is defined as follows.

$$f(X_{ij}) = \begin{cases} .5 * X_{ij} & ,X_{ij} < 0.2 \\ 0.1 + 1.5 * (X_{ij} - 0.2) & ,0.2 \le X_{ij} \text{ and } X_{ij} \le 0.7 \\ 1 + 0.5 * (X_{ij} - 1) & ,X_{ij} > 0.7 \end{cases} \qquad 5$$

The gray scale image is converted to index color map image and output image is of improved quality.

C) Double Threholding

This is used to generate mask. Here we convert grayscale image to binary image by setting pixels value in the range 0.2*255 – 0.7*255 according to eqn. (6). Here we set pixels value in the given range to white and remaining pixels to black. Thus this will discard most of the non-brain tissues. This is known as double thresholding as it uses two threshold levels upper and lowers [11].

$$g(x,y) = \begin{cases} 1 & ,0.2 * 255 \le f(x,y) \le 0.7 * 255 \\ 0 & ,otherwise \end{cases} \qquad 6$$

D) Region filling

It is normally used to fill the holes in the image. If tumor is present in the image then the eroded image will have holes in the brain tissue. So to get the complete skull strip image along with tumor this algorithm is applied. Here the enclosed or connected background pixels are converted to foreground pixels to remove the holes in the eroded image as shown in the given figure below:

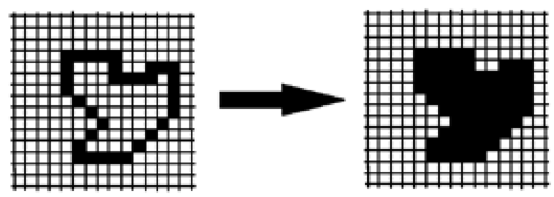

Figure 1: Region filling

(E) Level set algorithm

i) A new level set matrix function is applied to the given image.
ii) Then filtering of images is done to remove noise. Using neighborhood of size m by n to estimate local image mean and standard deviation uses Wieners filter-to-filter image pixel wise.
iii) Now size of image is determined with pixels values of rows and columns and final image is resizes by resize command.
iv) Finally, Objective level set function is applied and matrix values are modified exponentially until center of contour is converges. Distance matrix and new center is calculated at each iteration of new objective function until convergence.

5. Results and Discussion

Analysis and area of tumor is calculated using proposed methodology. This method has been applied on 10 different brain images whose results are given in table 1. Table 1 shows the list of all 10 original MRI brain images. Table 2 shows detected tumor images. In these images tumor part is highlighted with a dotted green line. Table 3 gives the area of tumor part present in every image in centimeter.

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Table 1: 10 Original MRI Images

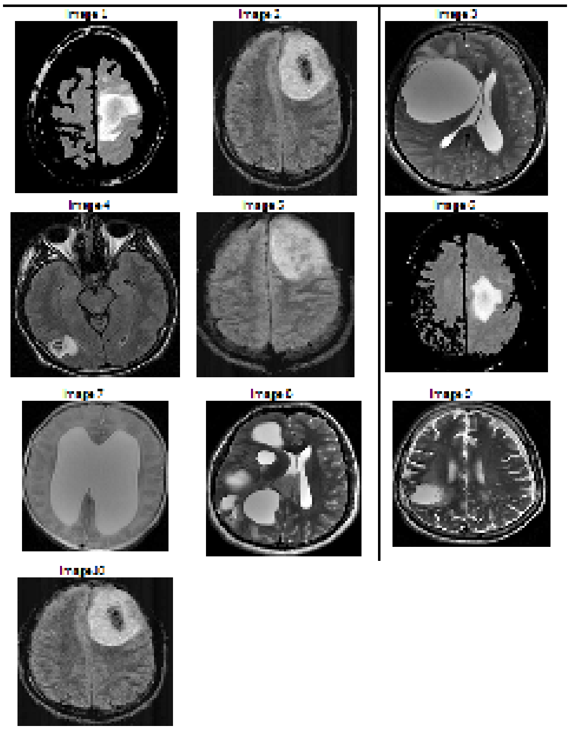

Table 2:Tumor detected images

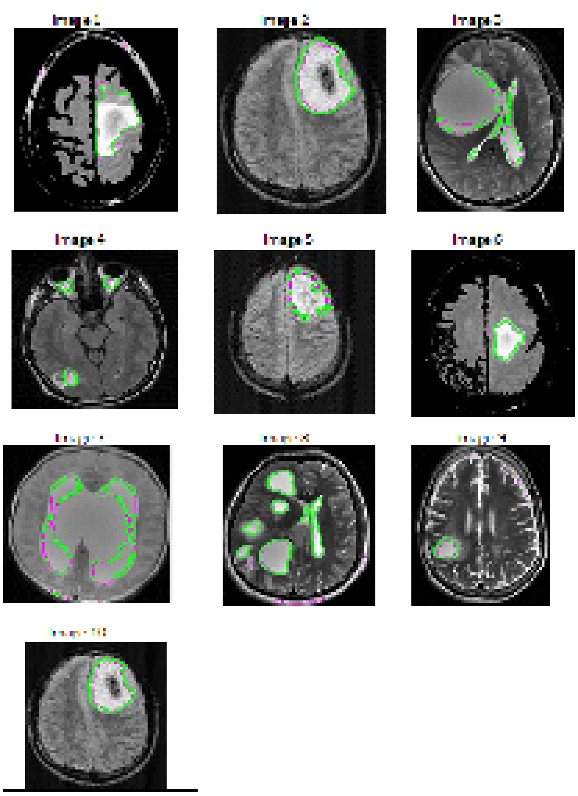

Table 3: Area of tumor

Images	Area of tumor in cm
1	36.13
2	65.73
3	31.16
4	1.67
5	26.93
6	28.99
7	79.43
8	45.79
9	24.50
10	61.50

6. Conclusions

Individually, fuzzy logic lead to time consuming process and level set method required manual intervention for calculation of active contour area. This paper presents a new level set method integrated with fuzzy clustering for brain tumor segmentation. This process is more robust as compare to other individual methods. In this process we reduce number of operations per iterations and improve the efficiency. Performance evaluation has been done on various MR images. The result confirms its effectiveness for brain tumor detection.

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