

Brain Tumor Detection using Level Set Segmentation

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Abstract –In medical image investigation, one of the essential problems is segmentation of structural sections. This paper presents a novel concept of tumor detection and also validated segmentation of 2D MRI Data. This method on the appropriate setting of parameters can segment the tumor. This method unlike others does not require any initialization in the tumor. Also the effectiveness of this approach is demonstrated by quantitative evaluations and visualization of the segmentation results. First, the work was carried over to calculate the area of the tumor with single slice of MRI data set and then it is extended to calculate the area of tumor from multiple image MRI data sets. Level set Segmentation and morphological operation is used for proper classification of medical data.

Keywords –Brain Tumor, Morphological Operations, MRI, ROI.

I. INTRODUCTION

The physicians and cancer researchers compare imaging studies from cases similar to a selected patient or a drawn query region and create a similarity measure which is relevant. It is important to perform complex statements with logical operations to combine different similarity measures and to specify different query regions, all without having expertise in MATLAB. It is also necessary to give the user an intuitive interface to specify a query region (whether on a study of a patient or on a brain atlas). The query region which can be drawn has also to consist of complex statements to specify a complete query region.

To obtain similarity between the drawn query region and the Region of Interest (ROI) such as the segmented tumor or edema, the voxel-set of the segmentations is stored in the database. A voxel-set of a segmented ROI belonging to one study contains about 20,000 voxels. For efficient retrieval the Database model has to be well designed. It is important to achieve a fast retrieval of thousands of data in an acceptable time; therefore the database tables must be indexed to reduce search time

One goal is to use machine learning methods to predict the locations of occult cancer cells to allow radiologists to refine the radiation therapy used to treat brain tumors; finding previous patients with similar tumors to a current patient and examining how the previous patients responded to treatment will help determine how to treat the current patient. Similarity based queries play an increasingly important role in medical training, research, and clinical decision making.

Similarity based retrieval is used by physicians who want to compare imaging studies from either a new patient or a self-selected query to those from a database of prior patients to help them to specify diagnosis, the tumor growth, and potential treatment options. Therefore it is important to support interactive queries of the tumor dataset by physicians and cancer researchers. An interactive query which provides the opportunity to do queries based on text data and to combine them to image-based similarity queries is the basis for significant analysis. Therefore a database is needed to store both the text-based and image-based brain tumor data.

II. PROPOSED METHOD

Steps for proposed algorithm are described in following headings.

A. Image acquisition

Images are obtained using MRI scan and these scanned images are displayed in a two dimensional matrices having pixels as its elements. These matrices are dependent on matrix size and its field of view. Images are stored in MATLAB and displayed as a gray scale image of size 256×256. The entries of a gray scale image are ranging from 0 to 255, where 0 shows the total black colour and 255 shows the pure white colour. Entries between this ranges vary in intensity from black to white.

For experimental purpose 30 female and 30 male patients were examined, all patients have ages ranging from 20 to 60 years. Their MRI scans were stored in the database of images in JPEG image formats.

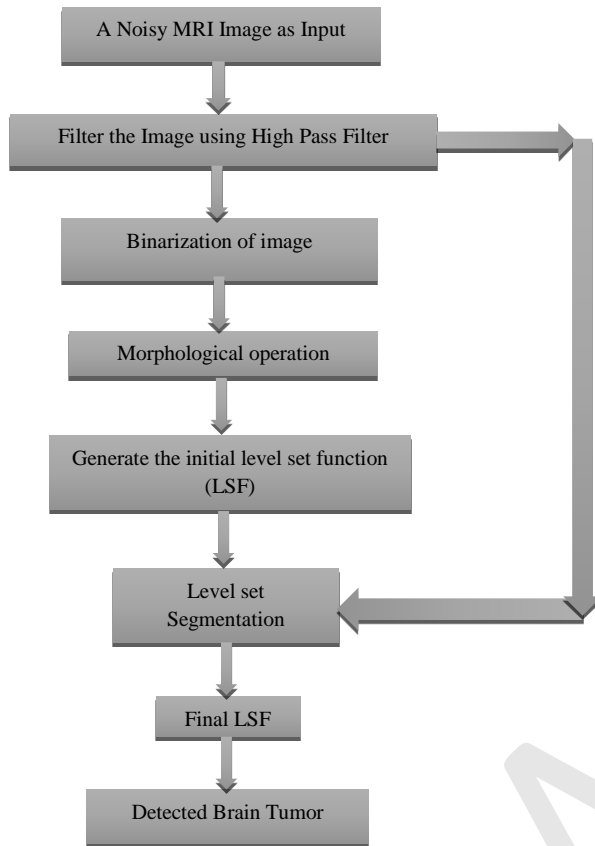


Figure 1: Flow chart of proposed work

B. Pre-processing

The first phase is to get the MRI image and application of pre-processing steps. There are various methods which come under this step; we will be dealing with only grey scale and filters. Basically pre-processing is done to remove noise and blurring as well as a ringing effect in order to get the enhanced and much clear image for our purpose. The filter which we have used is a high pass filter but as we are working on image samples that are required for the medical purpose. The high pass filter has to be passed with mask for better image, to achieve this we are using a sobel operator.

C. Level Set Segmentation

The Level Set Function is used here to robust the image under consideration towards noise condition, aptitude in extracting curved objects with complex topology and its clean numerical framework of multidimensional implementation. With the initialization of level function we generate the initial region of image as a rectangle. Level set evolution and object detection is further divided in three categories i.e. dilate marker, erode marker and Gradient Magnitude. The first two are subjected to

the Morphological Reconstructions (Mask, Marker) from which binary image is extracted.

Segmentation of an image I via active contours, also referred to as snakes [1], operates through an energy functional controlling the deformation of an initial contour curve $C(p)$, $p \in [0, 1]$ under the influence of internal and external forces achieving a minimum energy state at high-gradient locations. The generic energy functional for active contour models is expressed as:

$$E(C) = \alpha \int_0^1 |c'(s)|^2 ds + \beta \int_0^1 |c''(s)| ds - \lambda \int_0^1 |\nabla I(C(s))|^2 ds \quad (1)$$

Where (α, β, λ) are positive parameters. The first two terms control the rigidity and elasticity of the contour (defining the internal energy of the deformable object) while the last term attracts the model to high-gradient locations in the image I (defining the external energy of the model).

Active contour segmentation via minimization of the energy functional in Equation (1) is typically implemented with a parametric framework in which the deformable model is explicitly formulated as a parameterized contour on a regular spatial grid, tracking its point positions in a Lagrangian framework [2].

In their original paper from 1988 [26], Osher and Sethian introduced the concept of geometric deformable models, which provide an implicit formulation of the deformable contour in a level set framework. To introduce the concept of the level set framework we focus on the boundary-value problem of a close contour C deforming with a speed V along its normal direction:

$$|\nabla C| V = 1, V > 0 \quad (2)$$

Their fundamental idea is, instead of tracking in time the positions of the front $C(x, y)$ on a regular grid as:

$$(t) = \{(x, y) | C(x, y) = t\} \quad (3)$$

To embed the curve into a higher dimension function $\phi(x, y, t)$ such that:

1. At time zero the initial contour C_0 corresponds to the level zero of the function ϕ :

$$C_0 = \{(x, y) | \phi(x, y, 0) = 0\} \quad (4)$$

2. The function ϕ evolves with the dynamic equation:

$$\frac{\partial \phi}{\partial t} = |\nabla \phi| V \quad (5)$$

In this framework, at any time t , the front implicitly defined by:

$$(t) = \{(x, y) | \phi(x, y, t) = 0\} \quad (6)$$

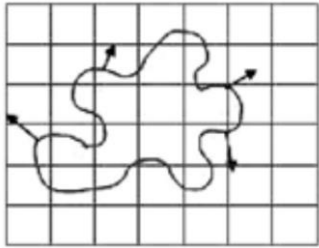
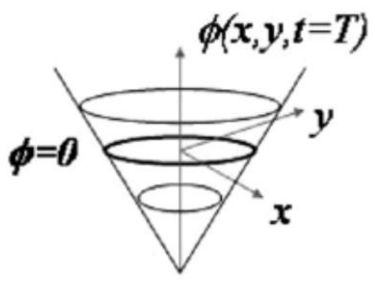
<p>Boundary Value Problem</p> $ \nabla C V = 1$ <p>Front: $\Gamma(t) = \{(x, y) C(x, y) = t\}$</p> <p>Speed: $V > 0$</p> 	<p>Initial Value Problem</p> $\phi_t + V \nabla\phi = 0$ <p>Front: $\Gamma(t) = \{(x, y) \phi(x, y, t) = 0\}$</p> <p>Speed: $\forall V$</p> 
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Figure 2: Correspondence between a parametric and implicit level-set formulation of the deformation of a contour with a speed term oriented along the normal direction

Corresponds to the solution of the initial boundary value problem defined parametrically in Eq. (3). This result is illustrated in Figure 2. The speed term is expressed as:

$$V = \text{div} \left(\frac{\nabla\phi}{|\nabla\phi|} \right) \quad (7)$$

Since its introduction, the concept of deformable models for image segmentation defined in a level set framework has motivated the development of several families of method that include: geometric active contours based on mean curvature flow, gradient-based implicit active contours and geodesic active contours.

III. SIMULATION AND RESULTS

The performance of proposed algorithms has been studied by means of MATLAB simulation.

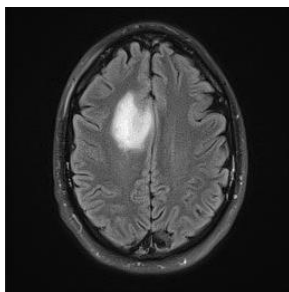


Figure 3: Input image

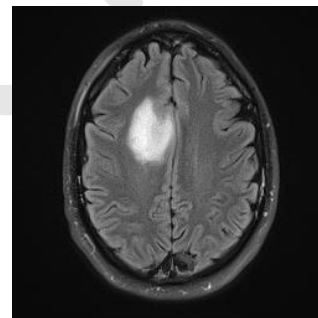


Figure 4: Acquired image

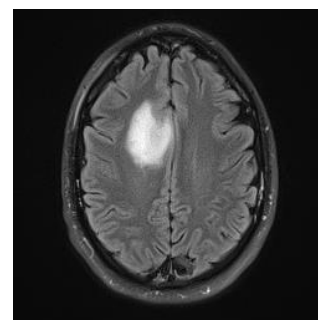


Figure 5: High pass filtered image

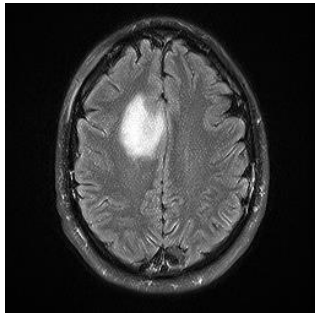


Figure 6: Enhanced image

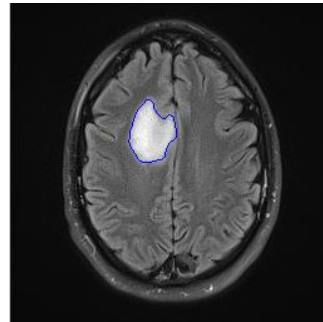


Figure 10: Iteration no. 63



Figure 7: Binary image

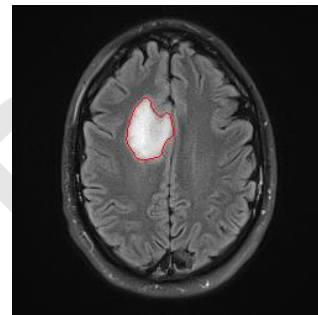


Figure 11: Original image with tumor region

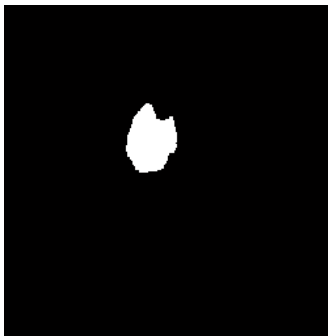


Figure 8: Morphed image with detected tumor region

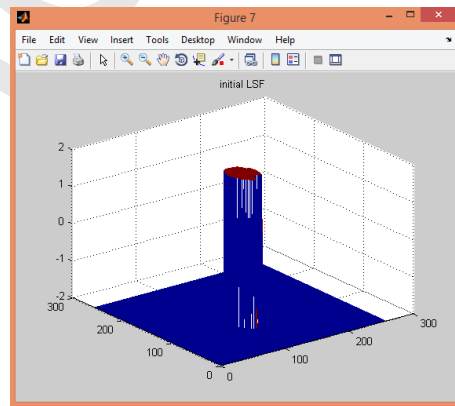


Figure 12: Initial LSF

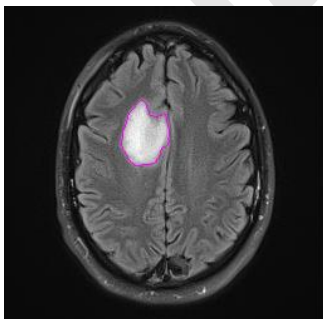


Figure 9: Original image with initial tumor region

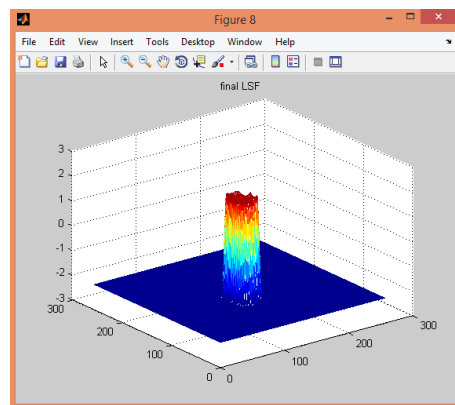


Figure 13: Final LSF

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 11, June 2016)

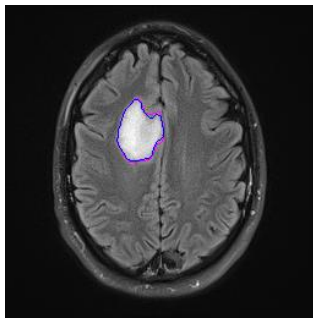


Figure 14: Original image with tumor region, before and after Level-set

Table 1: Result analysis

S. No.	Area (Pixels)	Mean	Variance
1	1330	203.3	669.6

IV. CONCLUSION

The simulation results show that Level Set Segmentation can successfully segment a tumor provided the parameters are set properly in MATLAB environment. Our Hybrid approach algorithm performance is better for the cases where the intensity level difference amongst the tumor and non-tumor sections are larger. It can likewise fragment non homogenous tumors giving the non-homogeneity is inside of the tumor segment. This work demonstrates that approaches designed at general purpose segmentation tools in medical imaging can be utilized for automatic segmentation of brain tumors. This research work outperforms than the previous research work (Zulpe et al. [4]) on the basis of area. In the proposed approach, performance of the system is evaluated using area, mean and variance. Here the evaluation analysis is increased by virtue of these two parameters; mean and variance, whose values are given in Table 1.

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