

## 3d Tumor Segmentation From Volumetric Brain Mr Images Using Level-Sets Method.

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### Abstract

*The main objective of this paper is to provide an efficient tool for delineating brain tumors in 3D magnetic resonance images. To achieve this goal, we use basically a level-sets approach to delineating 3D brain tumor. This paper involves implementing various steps of extracting the tumor from the 2D slices of MRI brain images by using level sets. First approach is based on contour information and second approach is based on region information.*

**Key words:** *Brain tumor, magnetic resonance (MR) image segmentation, 3D reconstruction, level sets, contour based, region based.*

### 1.Introduction

A brain tumor is an intracranial solid neoplasm, within the brain or the central spinal canal. Primary brain tumor begins within the brain tissue. A secondary brain tumor spreads from its original place to another part of the body. The american cancer society estimated that 18,500 people would be diagnosed with brain tumor and

that 12,760 men and women would die of brain cancer in 2005.

Magnetic resonance imaging (MRI), is a technique used in radiology to visualize internal structures of the body in detail. Because of its greater contrast between different soft tissues of the body, it is effectively used in assisting diagnosis, especially in evaluating brain tumor instead of using computed tomography.

The level set method is a numerical technique for tracking interfaces and shapes. The advantage of the level set method is that one can perform numerical computations involving curves and surfaces on a fixed cartesian grid without having to parameterize. Also, the level set method makes it very easy to follow shapes that change topology, for example when a shape splits in two, develops holes, or the reverse of these operations, all these make the level set method a great tool for modeling time varying objects, like inflation of an airbag, or a drop of oil floating in water.[1]

### 2.Related Works

An implicit representation of deformable surface models called the method of level sets. The level set method computes the motion of a moving interface by solving a partial differential equation (PDE) on a

volume. The use of level set as been widely documented in the medical imaging literature, and several works give more comprehensive reviews of the method and associated numerical techniques. For certain classes of application, level sets have several advantages over parametric models. Because they are implicit, level sets can change topology and deform far from their initial conditions without reparameterization. Finally, level sets allow for geometric surface deformation, which means that the results of a deformation process depend on the shape of the surface and the input data and not on some underlying parameterization. As with the original work on image segmentation by parametric deformable models, the level set approach to segmentation typically combines a data-fitting term with a smoothing term. However, there are alternatives. For instance, whitaker proposes a formulation that mimics parametric deformable models, in which level surfaces move toward edges in volumes.[2][3][4]

### 3.Methodology

We develop a first technique of 3D brain tumor segmentation by stacking a sequence of 2D tumor contours, detected by 2D level-sets method in the parallel cross-sectional MRI images. It consists on applying to each brain MRI slice the level-sets method in 2D and to propagate the result by taking as initial data the result of the preceding slice. This approach has several advantages such as simplicity to implement, it is fast, it requires less time than manual segmentation.[5]

The main stages of algorithm are

- Initialization of a curve around the tumor in the middle cross-sectional MRI images is called ‘main slice’ in this work.
- Run a level-sets algorithm in the main slice.
- The brain tumor boundary in the main slice is used as initial curve in its tow contiguous slices (one upper slice and one lower slice) and so forth.
- The algorithm stops when all the cross-sectional MRI images are processed. After all tumor boundaries are stacked and 3D tumor shape is reconstructed.

#### 3.1 3D level-sets method with contour information.

The first stage of this method is to initialize a small sphere around the border of the brain tumor. Then the level-Sets model evolves according to information related to edges in the volumetric brain MR images. This movement comes to its end when the deformable surface found the actual border of the brain tumor.

3D discret evolution equation of the level-set

$$\varphi_{ijk}^{n+1} = \varphi_{ijk}^n + \Delta t \left( \begin{array}{l} g_{ijk}(I) \varepsilon k_{ijk}^n [(D_{ijk}^{0x})^2 + (D_{ijk}^{0y})^2 \\ + (D_{ijk}^{0z})^2]^{1/2} + \\ \max(g_{ijk}(I) V_{0ijk}, 0) \nabla^+ \varphi + \\ \min(g_{ijk}(I) V_{0ijk}, 0) \nabla^- \varphi \end{array} \right)$$

where

$$\nabla^+ \varphi = \left[ \begin{array}{l} (\max(D_{ijk}^{-x} \varphi_{ijk}, 0))^2 + (\min(D_{ijk}^{+x} \varphi_{ijk}, 0))^2 \\ (\max(D_{ijk}^{-y} \varphi_{ijk}, 0))^2 + (\min(D_{ijk}^{+y} \varphi_{ijk}, 0))^2 \\ (\max(D_{ijk}^{-z} \varphi_{ijk}, 0))^2 + (\min(D_{ijk}^{+z} \varphi_{ijk}, 0))^2 \end{array} \right]^{1/2}$$

$$\nabla^- \varphi = \left[ \begin{array}{l} (\min(D_{ijk}^{-x} \varphi_{ijk}, 0))^2 + (\max(D_{ijk}^{+x} \varphi_{ijk}, 0))^2 \\ (\min(D_{ijk}^{-y} \varphi_{ijk}, 0))^2 + (\max(D_{ijk}^{+y} \varphi_{ijk}, 0))^2 \\ (\min(D_{ijk}^{-z} \varphi_{ijk}, 0))^2 + (\max(D_{ijk}^{+z} \varphi_{ijk}, 0))^2 \end{array} \right]^{1/2}$$

The curvature is given as

$$k = \frac{2\varphi_x \varphi_y \varphi_{xy} - \varphi_x \varphi_z \varphi_{xz} + 2\varphi_y \varphi_z \varphi_{yz}}{(\varphi_x^2 + \varphi_y^2 + \varphi_z^2)^{2/3}}$$

To stop the evolution of 3D level-sets model in the desired boundaries we used 3D version of the anisotropic diffusion filter in order to reduce noise without removing significant parts of the brain MRI volume and without evolving the deformable surface toward the brain tumor borders.[6]

### Disadvantages

This approach is related to leakage or overflow of the deformable surface in regions where overlapping intensities are present and that usually leads to poor detected results.

### 3.2 3D level-sets method with region information.

In the previous approach, the segmentation quality is not good, it means that the gradient information which is local information insufficient to control the

evolution of the level-Sets model. An alternative is to integrate statistical information related to regions in the brain MRI volume to improve the quality of brain tumor segmentation. The general principle is based on the evolution of a surface  $\Gamma$  which partitions the volume data into several regions of different statistical characteristics. A single deformable surface  $\Gamma$  allows segmentation into two regions  $\Omega_{in}$  and  $\Omega_{out}$  where,  $\Omega_{in}$  represents the region that circumscribed by the surface  $\Gamma$  and  $\Omega_{out}$  the outer region. The information that controls the evolution of the the new level-Sets model is usually based on statistical modelling of the various region in the volumetric data. We assume that the image  $I(x,y,z)$  defined on the domain  $\Omega$  is composed of two homogeneous regions of distinct values  $I_0$  and  $I_1$  and that the tumor region to detect corresponds to the region of intensity  $I_0$ . We denote the boundary of the tumor with intensity  $I_0$  by  $\Gamma$ . For a given surface  $\Gamma$  of the domain  $\Omega$ , we consider the following energy functional  $E(\Gamma)$ :

$$E(\Gamma) = \mu L(\Gamma) + \nu A(\Gamma) + \lambda_0 \int_{\Omega_{in}} |I_0 - c_0|^2 d\Omega + \lambda_1 \int_{\Omega_{out}} |I_1 - c_1|^2 d\Omega$$

Where  $c_0$  and  $c_1$  are equal respectively to the average value of inside and outside of surface  $\Gamma$ .  $L(\Gamma)$  and  $A(\Gamma)$  are the regularizing terms corresponding respectively to the length of the curve and the area of the object enclosed by the curve.  $\mu, \nu, \lambda_1, \lambda_2$  are fixed positive parameters.

Segmentation of the brain tumor from volumetric MRI image is performed via minimization of the energy functional. Minimization of the functional is

proceeded using a steepest gradient descent on a discrete spatial grid indexed with  $(i, j, k) \in \mathbb{R}^3$  and introduction of a temporal index (n) leads to an iterative scheme with the following equation of the level-Sets evolution model:

$$\varphi_{ijk}^{n+1} = \varphi_{ijk}^n + \nabla t \times \delta_\epsilon(\varphi_{ijk}^n) (-\mu k \varphi_{ijk}^n + \lambda_1 (I_{ijk} - c_1 \varphi_{ijk}^n)^2 + \lambda_2 (I_{ijk} - c_2 \varphi_{ijk}^n)^2)$$

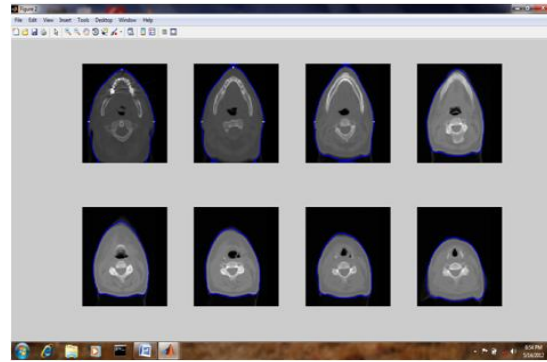
To segment the brain tumor using this approach ,we initialized an initial surface through its boundary. Then this surface evolves until reaching the actual border of the tumor. Several criteria can be incorporated to stop the process of segmentation: when the area of the deformable surface becomes constant or the volume of the region bounded by the deformable Surface becomes constant or Energy function  $E(\Gamma)$  reaches its minimum value. The latter Criterion is sufficient but it has a problem of computational cost. The convergence of the deformable surface to the tumor border implies that the area and the volume of deformable surface becomes constant. However, area and volume computational is less.

Then the level-Sets model evolves according to related region information in the image in order to plate itself on the surface of the tumor.[7]

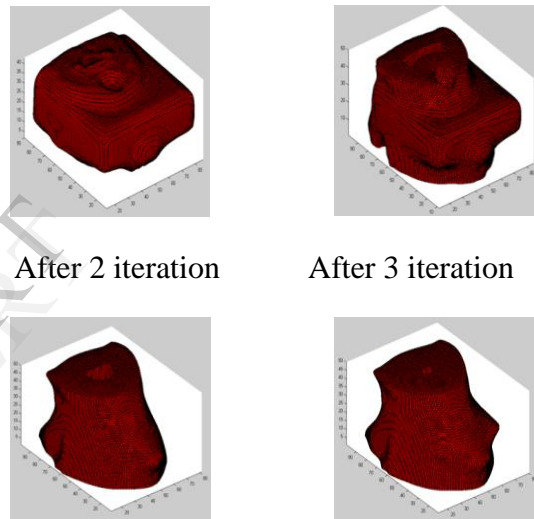
**Advantages**

Arbitrary initialization of the object anywhere in the image, no need for gradient information, self adaptation for inward and outward local motion.

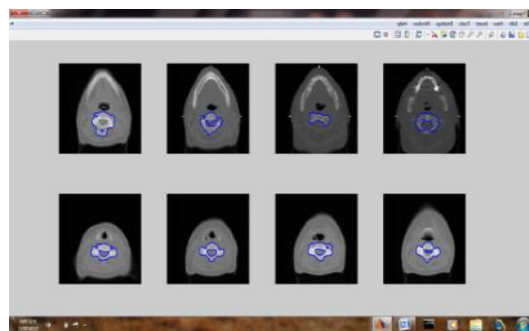
**4.Results**



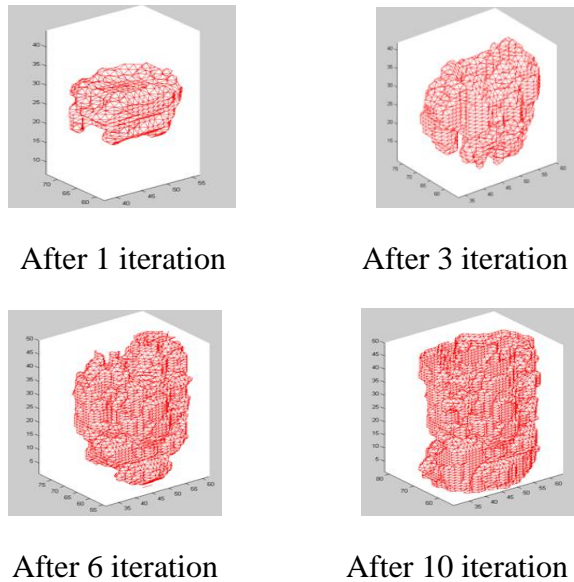
**Fig 1:** 2D Segmented Images Using Level Sets (Contour Based)



After 2 iteration      After 3 iteration  
After 6 iteration      After 10 iteration  
**Fig 2:** 3D Visualization of Reconstructed Brain Tumor(Contour Based)



**Fig 3:** 2D Segmented Images Using Level Sets (Region based)



**Fig 4:** 3D Visualization of Reconstructed Brain Tumor (Region Based)

## 5. Conclusion

We have presented a variational method, 3d level-sets applied to automatic segmentation of brain tumor in MRIs, using boundary and region based information of tumor to control the deformable surface propagation. The first approach used is the 3d reconstruction from its 2d contours using a sequence of 2d contours, detected by 2d level-sets method in the parallel cross-sectional MRI images. The second approach comes to improve the segmentation quality, based on carrying out the computation in 3d space and detecting the brain tumor region directly using 3d level-sets method.

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