3D Brain Tumor Segmentation Using Level-Sets Method and Meshes Simplification from Volumetric MR Images

K. Aloui, and M. S. Naceur

Abstract**—**The main objective of this paper is to provide an efficient tool for delineating brain tumors in three-dimensional magnetic resonance images. To achieve this goal, we use basically a level-sets approach to delineating three-dimensional brain tumors. Then we introduce a compression plan of 3D brain structures based for the meshes simplification, adapted for time to the specific needs of the telemedicine and to the capacities restricted by network communication. We present here the main stages of our system, and preliminary results which are very encouraging for clinical practice.

Keywords**—**Medical imaging, level-sets, compression, meshes simplification, telemedicine.

I. Introduction

SEGMENTATION in volumetric images is a tool allowing a diagnostics automation and as well will assist the expert in the qualitative and quantitative analysis. It's an important step in various applications such as visualization, quantitative analysis and image-guided surgery.

In the context of neuro-imaging, 3D segmentation of pathology and healthy structures is extremely important for surgical planning, qualitative and quantitative analysis such as volume measurements. Precise segmentation of pathological structures is a difficult task because brain tumors vary greatly in size and position, may have overlapping intensities with normal tissue and may be space occupying.

Traditionally, the boundary of a tumor in magnetic resonance imaging is usually traced by hand. Then the practitioner is confronted with a succession of boundary which he mentally stacked up to be made a 3D representation of the tumor. This reconstruction is inevitably subjective and becomes infeasible when dealing with large data sets, there is also an information loss in all the in three-dimensional images directions and then the process is time-consuming and very difficult.

Numerous segmentation methods have been developed in the past two decades for extraction of organ contours on medical images. Low-level segmentation methods, such as pixel-based clustering, region growing, and filter-based edge detection, requires additional pre-processing and post-processing as well as considerable amounts of expert intervention or information of the objects of interest [1].

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Recently, several attempts have been made to apply deformable models to brain image analysis. Indeed, deformable models refer to a large class of computer vision methods and have proved to be a successful segmentation technique for a wide range of applications.

Deformable models, on the other hand, provide an explicit representation of the boundary and the shape of the object. They combine several desirable features such as inherent connectivity and smoothness, which counteract noise and boundary irregularities, as well as the ability to incorporate knowledge about the object of interest [2, 3, 4]. However, parametric deformable must be re-parameterized dynamically to faithfully recover the object boundary and that it has difficulty dealing with topological adaptation such as splitting or merging model parts. Level-sets deformable models [5, 6, 7], also referred to as geometric deformable models, provide an elegant solution to address the primary limitations of parametric deformable models. These methods have drawn a great deal of attention since their introduction in 1988. Advantages of the contour implicit formulation of the deformable model over parametric formulation include: no parameterization of the contour, topological flexibility, good numerical stability and straightforward extension of the 2D formulation to n-D.

We will develop a technique of 3D segmentation of a brain tumor by the stacking of 2D boundary. It consists in applying to each slice the level-sets method in 2D and to propagate the result by taking as initial data the result of the preceding slice. It's the 3D reconstruction from 2D tumor contours using a sequence of 2D contours, detected by 2D level-sets method in the parallel cross-sectional MRI images.

The segmentation of volumetric brain MR image supplied with the 3D representations of the popular structures, adapted to computing post-treatments as the compression and the transmission. Seen the enormous quantity of information to be managed and stored, the rapid improvement of medical instrumentation and patient record management system, and seen capacities restricted by communication networks. This evolution in the hospital environment which the objective is to insure a better service for the patient and for the health professionals places very high demands on the networking and digital storage infrastructure of hospitals. In addition to having quite stringent requirements on the quality of the images displayed to the radiologist, much of the technical challenge resides in the necessity of displaying desired images as rapidly as possible. In this context a compression process adapted for time to the specific needs of the telemedicine and to the capacities restricted by network communication is necessary, in fact the 3D representation of brain structures segmented from the volumetric MR images are the triangular meshes, a simplification of these multi-resolution meshes [8, 9, 10] allows to decrease the size of files while preserving geometrical characteristics of these segmented structures.

II. 3D Tumor Segmentation Using 2D Level-Sets Method

The aim of this step is to extract "exactly" the tumor region. For this reason, we propose to use a deformable model algorithm based on level set technique, rely on two central embeddings; first the embedding of the interface as the zero level-set of a higher dimensional function, and second, the embedding (or extension) of the interface's velocity to this higher dimensional level-set function.

A. Level-sets method: Basic Algorithms

The level-set method was devised by Osher and Sethian in [5, 6] as a simple and versatile method for computing and analyzing the motion rely on partial differential equations (PDEs) to model deforming isosurfaces. These methods have applications in a wide range of fields such as visualization, scientific computing, computer graphics, and computer vision. Applications in visualization include volume segmentation, surface processing, and surface reconstruction.

Level-sets methods rely on two central embeddings; first the embedding of the interface as the zero level set of a higher dimensional function, and second, the embedding (or extension) of the interface's velocity to this higher dimensional level set function. More precisely, given a moving closed hyper surface $\Gamma(t)$, that is, $\Gamma : [0,\infty) \rightarrow \Re^N$, propagating with a speed F in its normal direction, we wish to produce an Eulerian formulation for the motion of the hyper surface propagating along its normal direction with speed F, where F can be a function of various arguments, including the curvature, normal direction, etc. Let $\pm d$ be the signed distance to the interface. If this propagating interface is embedded as the zero level set of a higher dimensional function φ, that is, let $\varphi(X, t=0)$, where $X \in \Re^N$ is defined by:

$$\varphi(X, t=0) = \pm d \qquad (1)$$

then an initial value partial differential equation can be obtained for the evolution of φ, namely

$$\varphi_t + F|\nabla \varphi| = 0 \qquad (2)$$

$$\varphi(X, t=0) \quad given \qquad (3)$$

This is the implicit formulation of front propagation given in [5]. As discussed in [6, 7].

There are certain advantages associated with this formulation. First, it is unchanged in higher dimensions; that is, for surfaces propagating in three dimensions and higher. Second, topological changes in the evolving front $\Gamma(t)$ are handled naturally; the position of the front at time t is given by the zero level-set $\varphi(x, y, z, t=0)$ of the evolving level set function. This set need not be connected, and can break and merge as t advances. Third, terms in the speed function F involving geometric quantities such as the normal vector n and the curvature k may be easily approximated through the use of derivative operators applied to the level set function, that is,

$$n = \frac{\nabla \varphi}{|\nabla \varphi|} \qquad (4)$$

$$\kappa = div\left(\frac{\nabla\varphi}{|\nabla\varphi|}\right) \qquad (5)$$

Fourth, the upwind finite difference technology for hyperbolic conservation laws may be used to approximate the gradient operators.

B. Level-sets method: Stop function

The original formulation of speed function is,

$$F = g(I)(v + \varepsilon k) \qquad (6)$$

v: is a constant term which makes the surface contract or expand.

k: is the mean curvature of the evolving front.

ε: is the entropy condition expressing the importance of regularization.

$g(I)$: is the data consistency term which ensures the propagating front will stop in the vicinity of the desired object boundaries. $g(I)$ Represents a "stop function" depend on the contents of the image and makes it possible to stop the evolution of the curve when this one manages on the borders of the object to detect.

$$g(I) = \frac{1}{1 + |\nabla \hat{I}|^p} \qquad (7)$$

Originally Î being the image settled by a Gaussian operator and p = 1 or 2. The values of $g(I)$ are near to 0 in the regions where the gradient is high and near to 1 in the regions of relatively constant intensity.

In some image slices, the boundary feature of the tumor is not salient enough and the image gradient information is weak. It usually causes the "boundary leaking" problem when we apply the level set method to detect the 3D tumor surface.

The problem of the Gaussian filtering is the smoothing of the entire image, destroys and moves edges.

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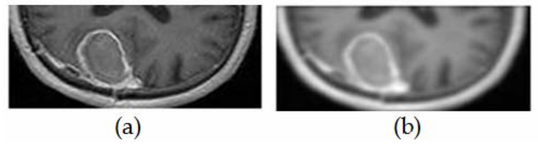


Fig. 1 Gaussian filters: destroys and moves edges. (a) Original image, (b) image smoothed by a Gaussian filter

We chosen then a filter which preserve the outline and limits the operation of smoothing to remedy the leaking problem, it is a non linear diffusion filter, proposed by P. Perona and J. Malik [19]. The action of such filter is given by the following not linear equation:

$$\frac{\partial I(X,t)}{*\partial t} = div\left(c(X,t).\nabla I(X,t)\right) \qquad (8)$$

$c(X,t)$, is called conduction coefficient.

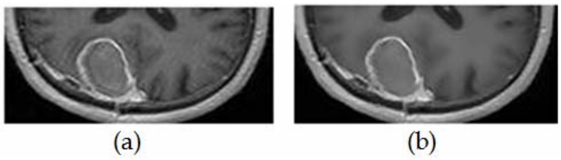


Fig. 2 Non linear diffusion filters: Preserves edges. (a) Original image, (b) image smoothed by an non linear diffusion filter

The following illustrations, shows the variation of the stop function given by the equation (7), where we apply a gaussien filter (a) and where we apply an anisotropique filtering (b).

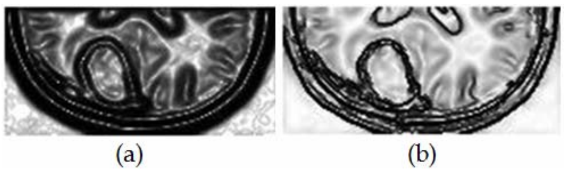


Fig. 3 Stop function *g(I).* (a) Using Gaussian filter, (b) using an anisotropic diffusion filter

C. 3D tumor reconstruction using 2D deformation

In this part, we start from small circle through the border of the brain tumor initialized in only one slice. Then, the level sets model evolves according to related boundaries information in the image in order to plate itself on the tumor boundary. The result is propagated towards the other slices by taking as initial data the result of the preceding slice.

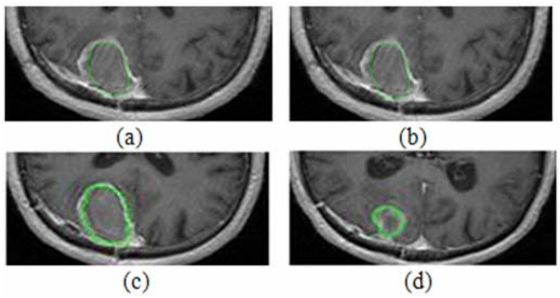


Fig. 4 Result of 2D segmentation: (a) slice 80, (b) slice 75, (c) slice 70, (d) slice 60

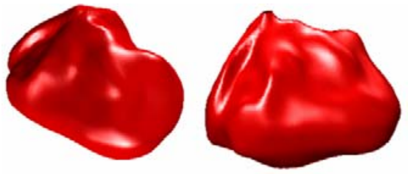


Fig. 5 3D brain tumor surface visualization stacking of 2D boundaries

The first approach used, is the 3D reconstruction from 2D contours using a sequence of 2D contours, detected by 2D level-sets method in the parallel cross-sectional MRI images. This method is simplest that one can make. It makes it possible to use active contours in the field 2D method which showed its robustness.

In this paper, only MRI data will be considered. Each MRI image dataset is 256 x 256 x 124. In addition, each pixel is represented by 8 bits. Different brain tumor cases are considered. Those data sets are provided from the new medical image and signal database, Medical Database for the Evaluation of Image and Signal processing (MeDEISA) [10].

III. 3D Surface Meshes Simplification

The segmentation of volumetric brain MR image supplied with the 3D representations of the popular structures, adapted to computing post-treatments as the compression and the transmission. The quantity of information in a volumetric MR images can be enormously reduced by modeling this volume by a set of surfaces representing border enter the various objects in this 3D image [11]. In fact the size of volumetric volume MR images 256*256*124 voxels can be remembered by a set for vertex ant faces represents the surface meshes of 3D brain tumor. Surface mesh simplification [12,13,14] is the process of reducing the number of faces used in the surface while keeping the overall shape, volume and boundaries preserved as much as possible.

The simplification meshes algorithm which we used in this work it is the halfedge collapse method [15,16]. Roughly speaking, the method consists of iteratively replacing an edge with a single vertex, removing 2 triangles per collapse. Given an edge 'FE' joining vertices 'F' and 'E', the edge-collapse operation replaces 'FE','F' and 'E' for a new vertex 'R', while the halfedge-collapse operation pulls 'F' into 'E', dissapearing 'e' and leaving 'E' in place. In both cases the operation removes the edge 'e' along with the 2 triangles adjacent to it.

Edges are collapsed according to a priority given by a cost function [17,18], and the coordinates of the replacing vertex are determined by another placement function. The algorithm terminates when a stop predicate is met, such as reaching the desired number of edges.

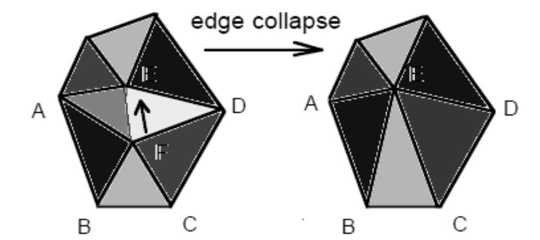


Fig. 6 Edge collapse principle

The purpose of meshes simplification of the meshing is to guarantee a weakest coding cost to accelerate some tasks as the 3D graphic reconstruction, the transmission on a communication channel by preserving the geometrical characteristics of the tumor so that it remains adapted to later treatments.

The simplification process is controlled by the tumor geometrical measure of the tumor in the 3D MR images, we notice a light variation of the tumor volume, the area of the surface, the area of the convex surface as well as a small movement of the centre of the meshes gravity center, From a compression ratio superior to 50, the variation of these geometrical characteristics become unacceptable and the meshing tends to lose its original shape.

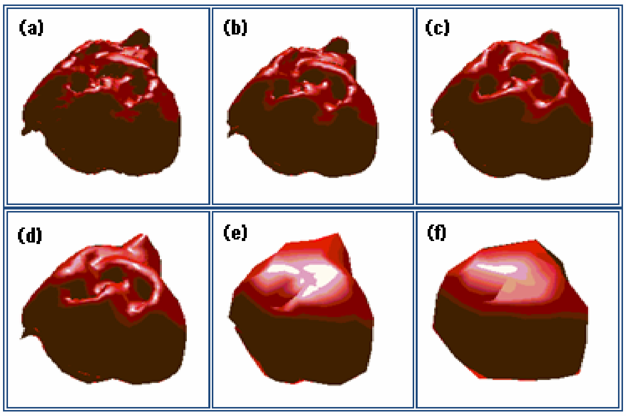
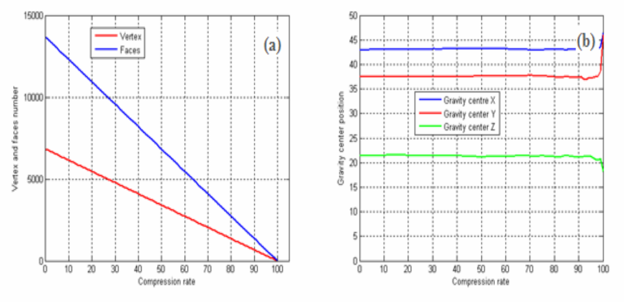


Fig. 7 Exemple of 3D tumor surface meshes simplification, (a) original 3D tumor surface meshes (= 6834 vertices 13672 faces), (b) 49% (3484 vertices 6972 faces), (c) 79% (1433 vertices 2870 faces), (d) 87% (749 vertices 1502 faces), (e) 97% (203 vertices 410 faces), (f) 98% (134 vertices 272 faces)



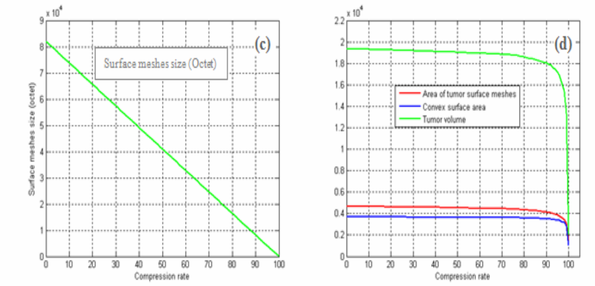


Fig. 8 Influence of the meshes simplification on the geometrical characteristics of the tumor and the meshes size

IV. Conclusion

We have presented a variational method, 3D level-set applied to automatic segmentation of brain tumor in MRIs. The segmentation of volumetric brain MR image supplied with the 3D representations of the popular structures, adapted to computing post-treatments as the compression and the transmission. We have presented surface simplification; we maintain that the topology and sharp surface features of the model should be preserved adaptively. The simplification meshes algorithm which we used in this work it is the half edge collapse method controlled by the tumor geometrical measure as meshes area and volume considered an important parameter such as, storage, transmission, visualization, and quantitative analysis.

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