3D Segmentation, Compression and Wireless Transmission of Volumetric Brain 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 and set up compression-transmit schemes to distribute result to the remote doctor. To achieve this goal, we use basically a level-sets approach to delineating brain tumors in three-dimensional. Then introduce a new compression and transmission 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 wireless 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, wireless transmission.

I. Introduction

THE advanced technology of computing system was followed by the rapid improvement of medical instrumentation and patient record management system. The typical examples are hospital information system (HIS) and picture archiving and communication system (PACS), which computerized the management procedure of medical records and images in hospital environment. 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, this paper addressed the set up of a chain for 3D tumor segmentation from volumetric brain MR images, compression and wireless transmission of results to the remote doctor. This present work introduce a new transmission plan of 3D brain structures, adapted for time to the specific needs of the telemedicine and to the capacities restricted by wireless network communication.

This paper is divided into 3 party, the first show the process of 3D segmentation of the brain tumor, the second concerns the simplification meshes process adapted for time to the specific needs of the telemedicine and to the capacities restricted by wireless network communication and the third watch the importance of the use of the wireless networks in the hospital environment to insure a rapidly and one better service for the patient and for the health professionals.

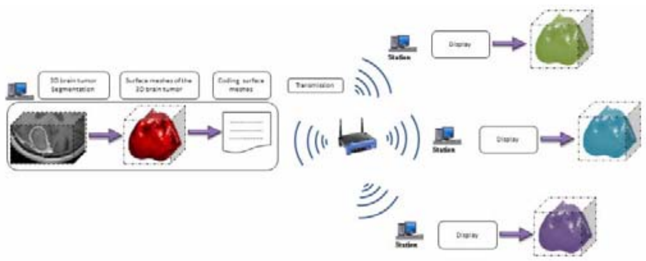

Fig. 1: Chain for 3D tumor segmentation from volumetric brain MR images, compression and wireless transmission in a hospital environment.

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].

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.

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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.

To obtain the 3D tumor surface, we stacked up the 2D tumor contours detected by 2D level-sets method applied 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 and seen capacities restricted by communication of the wireless networks, a process of compression 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. The choice of the FTP protocol [11] comes from its simplicity of implementation, it‘s used to exchange and manipulate files over a TCP computer network. The major advantage of this choice is that this FTP protocol allows verifying the integrity of the data passed on between the transport coat and the MAC layer to preserve the quality of the transmitted structures.

II. 3D TUMOR SEGMENTATION USING LEVEL-SETS METHOD

A. Level-set 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:

$$\varphi(X, t = 0) = \pm d \tag{1}$$

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

$$\varphi_t + F|\nabla \varphi| = 0 \tag{2}$$

$$\varphi(X, t = 0) \quad given \tag{3}$$

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,

$$n = \frac{\nabla \varphi}{|\nabla \varphi|} \tag{4}$$

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

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

B. Level-set Method: Stop function

The original formulation of speed function is,

$$F = g(I)(v + \varepsilon k) \tag{6}$$

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.

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

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.

The simplest solution to obtain the 3D tumor surface is to stack up a sequence of 2D tumor contours, detected by 2D level-sets method in the parallel cross-sectional MRI images. It consists in applying to each slice the level sets method. 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. This method goes very well but it has two defects major, there is no interaction between the slices and surface must be cylindrical. This approach is simplest that one can make. It makes it possible to use active contours in the field 2D method which showed its robustness. However, an evolution was necessary to the glance of its defects following the results obtained and the forms being able to be treated. The second approach based on carry out the computation in 3D space and detects the 3D tumor surface directly using 3D level-sets method. The level sets model evolves according to related boundaries information but 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.

In second place, we will improve quality of the segmentation by using the level sets method in 3D when the level sets model evolves according to related regions information in the image in order to plate itself on the surface of the tumor.

III. 3D LEVEL SETS METHOD WITH REGIONS INFORMATION

The proposed method is similar to the segmentation with a deformable model with a two-phased image, combining the following advantages: arbitrary initialization of the object anywhere in the image, no need for gradient information [9], self adaptation for inward and outward local motion.

Assume that the image $I(x,y,z)$ defined on the domain Ω is composed of two homogeneous regions of distinct values I_0 and I_1 that the object to detect corresponds to the region of intensity I_0. We denote the surface of the object with intensity I_0 by S_0. For a given surface S of the domain Ω, we consider the following energy functional $E(S)$:

$$E(S) = \mu L(S) + \nu A(S) + \lambda_0 \iint_{inside(S)} \left|I - c_0\right|^2 d\Omega + \lambda_1 \iint_{outside(S)} \left|I - c_1\right|^2 d\Omega \quad (8)$$

Where c_0 and c_1 are equal to the average value of intensity I inside and outside of S. $L(S)$ and $A(S)$ are the regularizing terms corresponding to the length of the curve and the area of the object enclosed by the curve. $\mu, \nu, \lambda_0, \lambda_1$ are fixed positive parameters.

The minimum of this energy is achieved for $S = S_0$, when the two terms tend to zero:

$$\min_{S}\left(E(S)\right) = E(S_0) \approx 0 \quad (8)$$

A. Level-sets formulation and Principal Steps of the Segmentation Algorithm

Segmentation of the MRI volume data is performed via minimization of the energy functional defined in Eq. (8). Minimization of the functional via steepest gradient descent on a discrete spatial grid indexed with $(i, j, k) \in \Re^3$ and introduction of a temporal index n leads to an iterative scheme with the following equation of evolution of the level-sets function:

$$\varphi_{i,j,k}^{n+1} = \varphi_{i,j,k}^{n} + \Delta t * \delta_{\varepsilon}\left(\varphi_{i,j,k}^{n+1}\right) * \begin{bmatrix} - \mu Force_{curvature}\left(\varphi_{i,j,k}^{n+1}\right) + \nu \\ + \lambda_0\left(I_{i,j,k} - c_0\left(\varphi_{i,j,k}^{n+1}\right)\right)^2 \\ + \lambda_1\left(I_{i,j,k} - c_1\left(\varphi_{i,j,k}^{n+1}\right)\right)^2 \end{bmatrix} \quad (9)$$

The sequence of function φ^n for $n \geq 0$ is constructed as follows:

(a) Start with $n = 0$. Initialize with a set of points a surface S_0 in the volumetric image domain.

(b) Define φ^0 as the signed distance function with zero-level defined at the location of the surface S_0.

(c) Compute $c_0(\varphi^n)$ and $c_1(\varphi^n)$ as the average of the function φ^n on the domains defined by $\varphi^n \prec 0$ and $\varphi^n \succ 0$ respectively.

(d) Compute the curvature term for φ^n.

(e) Solve Eq. (9) to obtain φ^{n+1}.

(f) Check whether the solution is stationary. Iterate for $n = n + 1$ if not.

The final zero-level is computed as the isosurface of the volume function φ^n at level zero.

B. Result

This method consists in initializing a small sphere through the border of the brain tumor. Then the level sets model evolves according to related regions information in the image in order to plate itself on the surface of the tumor.

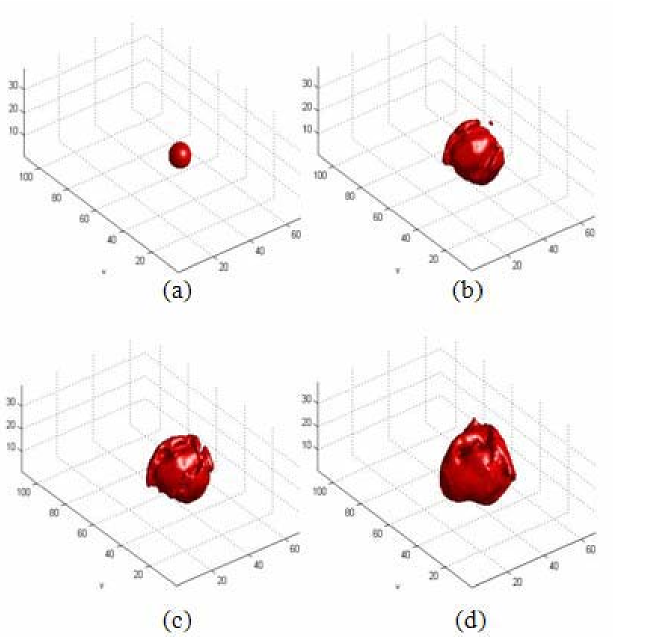

Fig. 2: 3D visualization of the surface of the brain tumor obtained by level sets method: (a) initialization, (b) iteration 80, (c) iteration 180, (d) iteration 300.

The following representation shows the segmentation result on some slicers.

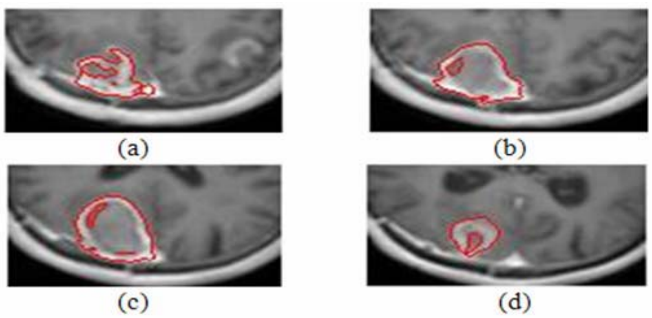

Fig. 3: Result of 2D segmentation: (a) slice 32, (b) slice 40, (c) slice 50, (d) slice 70.

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].

IV. 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.

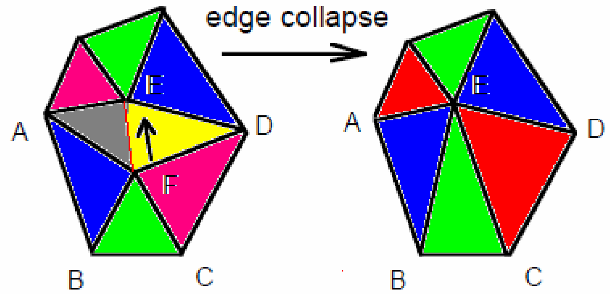

Fig. 4: Result of 2D segmentation: (a) slice 32, (b)

Fundamental algorithm

```
Edge collapse-algorithm
until (reach approximation index)
{
find the edge whose collapse
introduce the least error measure[17];
collapse that edge into one vertex;
}
return (base mesh);
Display surface meshes:
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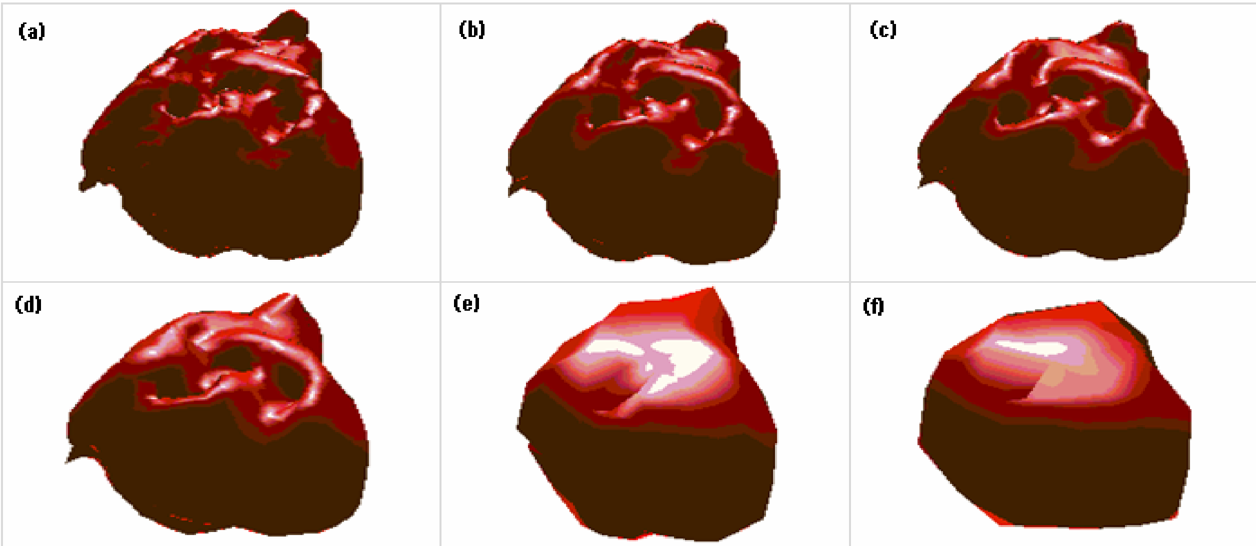

Fig. 5: Exemple of 3D tumor surface meshes simplification, (a) original 3D tumor surface meshes (= 6834 vertices 13672 faces), (b) 49% (3484 vertices 6972 faces), (c) 79% (1433 vertices 2870 faces), (d) 87% (749 vertices 1502 faces), (e) 97% (203 vertices 410 faces), (f) 98% (134 vertices 272 faces).

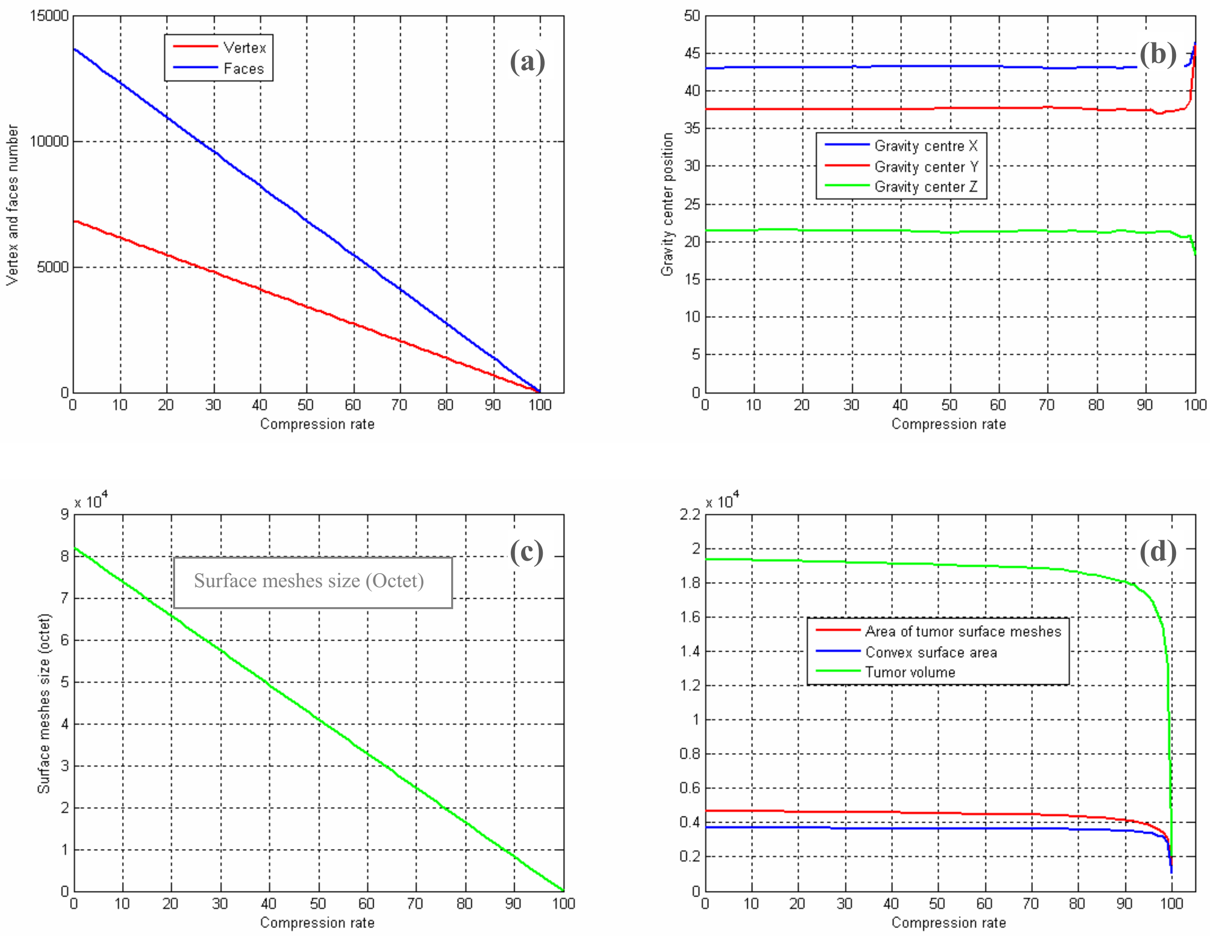

Fig. 6: Influence of the meshes simplification on the geometrical characteristics of the tumor and the meshes size.(a) Face and vertices number, (b) Gravity center of 3D tumor surface, (c) Surface meshes size, (d) Geometrical features of 3D tumor shape.

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.

V. Wireless transmission of 3D structures

Wireless transmission should be a good choice to replace cable connections of the coil arrays to minimize their cross talks. In recent years, several proposals of using wireless transmission for MRI have been reported [5] and [6] : Today, the hospital environment generally is characterized by a strong development of the "nomadicité". The employees are equipped with laptops and spend more time to work within team's multi-functionality and geographically scattered. The company can benefit from the deployment of a system WLAN as the mobile access and the flexibility of configuration. In this part File Transfer Protocol (FTP) is a network protocol used to transfer data from one computer to another through a local network, an FTP client may connect to an FTP server to manipulate files content the surfaces meshes on that server. FTP client's use a passive mode FTP connection to the server to avoid issues with their firewall.

VI. 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. Because today, the hospital environment generally is characterized by a strong development of the "nomadicité", a good choice to replace cable connections of the coil arrays is the Wireless transmission. In this work we presented a new chain for 3D tumor segmentation from volumetric brain MR images, compression and wireless transmission in a hospital environment to allowing a diagnostics automation and as well will assist the expert in the qualitative and quantitative analysis and computerizing the management procedure of medical records and images in hospital environment.

References

[1] T. McInerney and D. Terzopoulos, "Deformable models in medical image analysis: A survey," Medical Image Analysis, vol. 1, pp. 91-108, 1996.

[2] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," International Journal of Computer Vision, vol. 1, pp. 321-331, 1987.

[3] C. Xu, D. Pham, and J. Prince, "Image segmentation using deformable models.," in Handbook of Medical Imaging, vol. 2: SPIE, 2000, pp. 129-174.

[4] T. McInerney and D. Terzopoulos, "Topologically adaptable snakes," in the Proceedings of 5th International Conference on Computer Vision, pp. 840-845, 1995.

[5] S. Osher and J. A. Sethian, Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton–Jacobi formulations, J. Comput. Phys. 79, 12 (1988).

[6] J. A. Sethian, Numerical methods for propagating fronts, in Variational Methods for Free Surface Interfaces,

[7] J. A. Sethian, Curvature and the evolution of fronts, Commun. Math. Phys. 101, 487 (1985).A. Alpher. Frobnication. Journal of Foo, 12(1):234–778, 2002.

[8] R. Malladi, J. A. Sethian, and B. C. Vemuri, "Shape modeling with front propagation: A level set approach," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 17,no. 2, pp. 158–175, 1995.

[9] El. Angelini and al, Segmentation of Real-Time Three-Dimensional Ultrasound for Quantification of Ventricular Function: A Clinical Study on Right and Left Ventricles, Ultrasound in Med. & Biol., Vol. 31, No. 9, pp. 1143–1158, 2005

[10] Medical Database for the Evaluation of Image and Signal processing (MeDEISA),http://www.istia.univangers.fr/LISA_MeDEISA/IEEE_FRANCE_EMB/

[11] D.Saupe, J.Kuska. Compression of Isosurfaces for Structured Volumes. VMV 2001 : 333-340 Stuttgart, Germany 2001.

[12] O. Devillers et P.-M. Gandoin. Geometric compression for interactive transmission. Dans IEEE Visualization 2000 Conference Proc., 2000.

[13] P.-M. Gandoin et O. Devillers. Progressive lossless compression of arbitrary simplicial complexes. ACM Transactions on Graphics, 21 :372–379, 2002. SIGGRAPH '2002 Conference Proceedings.

[14] C. Touma et C. Gotsman. Triangle mesh compression. Dans Graphics Interface 98 Conference Proc., pages 26–34, 1998.

[15] D. Cohen-Or, D. Levin, et O. Remez. Progressive compression of arbitrary triangular meshes. Dans IEEE Visualization 99 Conference Proc., pages 67–72, 1999.

[16] P. Alliez et M. Desbrun. Progressive compression for lossless transmission of triangle meshes. Dans SIGGRAPH 2001 Conference Proc., 2001.

[17] H. Hoppe, T. DeRose, T. Duchamp, J. McDonald, et W. Stuetzle. Mesh optimization. Dans SIGGRAPH 93 Conference Proc., 1993.

[18] H. Hoppe, "Progressive Meshes", SIGGRAPH '96 Proc., pp. 99-108, August 1996.

[19] W.Peuch Evaluation d'une application de transmission d'images médicales avec un réseau sans fil 3rd International Conference: Sciences of Electronic, Technologies of Information and Telecommunications March 27-31, 2005 – TUNISIA

[20] S.Lee & T. Lee & G.Jin & J.Hong. An Implementation of Wireless Medical Image Transmission System on Mobile Devices. J Med Syst (2008) 32:471–480