A Surface Reconstruction Approach Based on Multi-Resolution Methods and T-Surfaces Framework

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ABSTRACT

In this paper we present a new approach which integrates the T-Surfaces framework and a multi-resolution method in a unified methodology for segmentation and surface reconstruction. For noisy images, we can improve the result by anisotropic diffusion. If some manual intervention is required to complete the reconstruction, we take advantage of the topological capabilities of T-Surfaces to enable the user to modify the topology of a surface

Keywords: Surface Reconstruction, Segmentation, Multi-Resolution, T-Surfaces

1 INTRODUCTION

Parametric Deformable Models, which includes the popular *snake models* [2] and deformable surfaces [5], are well known techniques for boundary extraction and tracking in 2D/3D images.

Recently, McInerney and Terzopoulos [3] proposed the T-Surfaces/T-Snakes model to add topological capabilities (*splits and merges*) to a parametric model. The basic idea is to embed a discrete deformable model within the framework of a simplicial domain decomposition of the image domain. Also, T-Surfaces depends on some threshold to define a normal force which is used to drive the model towards the targets [3].

Based on T-Snakes framework we proposed in [1] a segmentation approach for 2D images based on multi-resolution methods and the T-Snakes model.

In this work we firstly extend that approach for 3D through the T-Surfaces. Thus, we also assume a scale restriction for the targets. In a first stage, we use this restriction to define a coarsest image resolution that guarantees not split the objects. From the corresponding grid, we make a simple CF triangulation of the image domain. The low resolution image field is thresholded to get a binary function, which we call an *Object Characteristic Function*. Then, a simple continuation method is used to extract a set of closed polygonal surfaces which contain the anatomical structures. We demonstrate and explore the method in the experimental results.

2 T-SURFACES

The T-Surface approach is composed basically by three components [3]: a triangulation of the domain of interest, in our case a closed subset $D \subset \Re^3$, a particle model of the deformable surface and a *characteristic function* which distinguishes the interior ($Int(S)$) from the exterior ($Ext(S)$) of a surface S: $\chi(p) = 1$ if $p \in Int(S)$ and $\chi(p) = 0$, otherwise, where p is a node of the triangulation.

In this framework, the reparameterization of a surface is done by [3]: 1)taking the intersections points of the surface with the simplicial grid; 2)carrying out topological changes by tracing the simplices in which the characteristic function changes value (*traverse simplices*); 3)For each traverse edge choose an intersection point. These points will be connected to form a closed triangular mesh.

The mesh nodes are linked by springs with a natural length null. Hence, given the deformation $r_{ij} = \|v_i(t) - v_j(t)\|$ we define a tension force given by:

$$\overrightarrow{\alpha_i} = c \sum_j \overrightarrow{r}_{ij}, \quad (1)$$

where c is a scale factor. The model also has a normal and image forces [3] given respectively by:

$$F_i = k\,(sign_i)\,n_i,\; f_i^t = -\gamma \nabla \|\nabla I\|^2, \quad (2)$$

where n_i is the normal vector at node i, $sign_i = +1$ if $I(v_i) > T$ and $sign_i = -1$ otherwise (T is an image intensity threshold), and k, γ are scale factor.

The evolution of the surface is governed by the following dynamical system:

$$v_i^{(t+\Delta t)} = v_i^t + h_i \left(\overrightarrow{\alpha_i}^t + \overrightarrow{F_i}^t + \overrightarrow{f_i}^t \right), \quad (3)$$

where h_i is an evolution step. During the T-Surfaces evolution, some grid nodes become interior to a surface. Such nodes are called *burnt nodes* and its identification is fundamental to update the characteristic function [3]. To deal with self-intersections of the surface the T-Surface model incorporates an entropy condition: *once a node is burnt it stays burnt.*

3 OUR METHOD

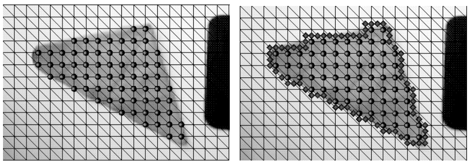
Let's suppose that the intensity (grey level) patterns of an object O (or of the background) can be characterized by a threshold T or some statistics (mean μ and variance σ) of the image field I [1, 3].

Firstly, we assume a local scale property. Given a point $p \in O$, let r_p be the radius of a hyperball B_p which contains p and lies entirely in the object region. We assume that $r_p > 1$, for all $p \in O$.

This local scale property implies that we can reduce the resolution of the image without losing the objects of interest. Let's see a simple example pictured on Figure 1.

In this case we have a threshold which identifies the object ($T < 150$). In the Figure 1(a) we have a CF triangulation whose grid resolution is 10×10.

Now, we can define a simple function, called a *Object Characteristic Function*, as follows: $\chi(p) = 1$ if $I(p) < T$ and



(a) (b)

Figure 1: (a) Original image and Characteristic Function. (b) Boundary approximation.

$\chi(p) = 0$, otherwise, where p is a node of the triangulation.

We can do a step further, shown in Figure 1(b), where we present a curve which belongs to the triangles in which the characteristic function (marked nodes) changes its value. Observe that this curve approximates the boundary we seek.

This scheme is adaptive in the sense that resolution can be increased inside the curve extracted if necessary. To increase the resolution we just refine the coarser grid and sample the image over the grid nodes corresponding.

The generation of that curve (or surface for 3D) can be done by a simple continuation algorithm which starts from a seed traverse simplex and attempts to trace the surface into neighboring simplices.

We can summarize the segmentation/surface reconstruction method above in the following steps: (1) Extract region based statistics; (2) Coarser image resolution and Triangulation; (3) Define the *Object Characteristic Function*; 4) Polygonal surface(s) extraction; 5) Apply T-Surfaces model.

4 EXPERIMENTAL RESULTS

Firstly, we take a synthetic $150 \times 150 \times 150$ image volume composed by a sphere with radius 30 and an ellipsoid with axes 45, 60 and 30 inside an uniform noise specified by the image intensity range 0-150.

Figures 2(a),(b) show the result for steps (1)-(4) applied to this volume after anisotropic diffusion and the cross section to the slice 40, respectively. This is an interesting pre-processing method because it enables to blur small discontinuities as well as to enhance edges [4]. Figures 2(c),(d) show the final result and the corresponding cross section to the slice 40.

An important point becomes clear in this example: the topological abilities of T-Surfaces enable to correct the defects observed in the surface extracted through the steps (1)-(4). Hence, after few interactions, the method gives one connected component which is a better approximation of the target.

The T-Surface parameters are: $c = 0.65$, $k = 1.32$ and $\gamma = 0.01$. The grid resolution is $5 \times 5 \times 5$, freezing point is set to 15 and threshold $T \in (120, 134)$ in equation (2). The number of deformation steps for T-Surfaces was 17 (the model evolution can be visualized in http://virtual01.lncc.br/ rodrigo/tese/elipse.html).

Figure 3(a) shows an example where the steps (1)-(5) where not able to complete the segmentation. This can be resolved by user interaction through the following method: (a) Define a cutting plane; (b)Set to zero the grid nodes belonging to the triangles that the plane cuts and that are interior to the T-Surface; (c)Apply steps (4)-(5) above. The grid nodes set to zero becomes burnt nodes. Thus, the entropy condition will prevents intersections of the two T-Surfaces generated. Hence, we can efficiently guarantee that these surfaces will not merge again during the evolution. Figure 3(b) shows the final result. The parameters are the same of the last example.

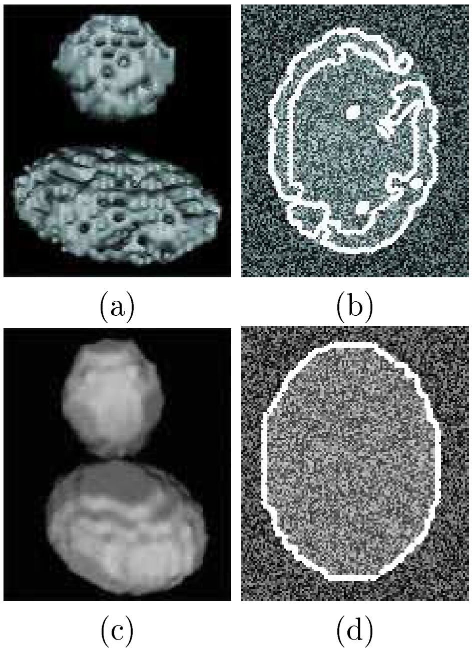


Figure 2: (a) Result with Anisotropic Diffusion for steps (1)-(4). (b) Cross section for slice 40. (c)-(d) Final result and cross section.

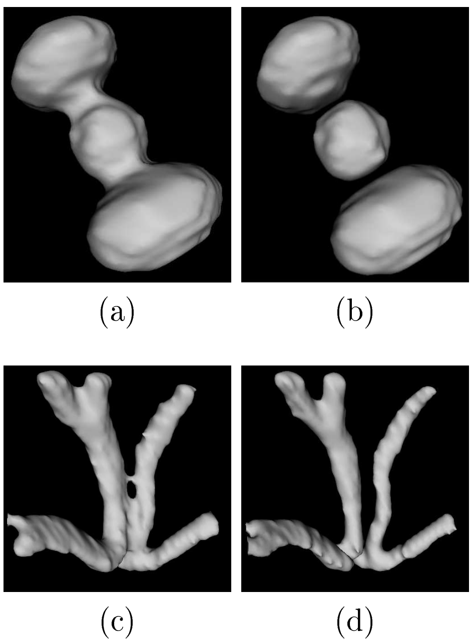


Figure 3: (a)-(b) Partial and final result after manual cut. (c) Artery segmentation without and (d) after anisotropic diffusion

Finally, we segment an artery from an $155 \times 170 \times 165$ image volume obtained from the Visible Human project. The grid resolution is $4 \times 4 \times 4$ and freezing point is set to 10. The (correct) result is pictured on Figure 3(d) which was obtained through anisotropic diffusion. An important point to highlight is that by initializing the T-Surfaces with steps (1)-(4) we achieve speed ups even for finer grid resolutions.

Future directions for this work will be to generalize the user interaction method by substituting the plane by a scalpel and allowing the user to drag the scalpel.

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