Combined watershed and deformable simplex mesh for volumetric reconstruction

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Summary
Several geometric deformable models have been proposed to deform and manipulate 3D meshes to fit medical object. However, they reveal poor convergence to concave boundaries and necessitate manual interaction to initialize the model. Generally when dealing with volumetric reconstruction, one has to solve two synchronized problems: a segmentation problem consisting in the delineation (fit image boundaries) and an interpolation problem consisting in recovering the missing data. In this paper, we propose a deformable reconstruction system for 3D medical object and we address factors that influence evolution of deformable models. The input to our system is a set of lines extracted with watershed algorithm and deformable simplex meshes that take into account this prior knowledge.

Keys words:
Volumetric reconstruction, Deformable models, Watershed algorithm, Simplex meshes.

1. Introduction

Over the last decade, there has been increasing research activity to address the tremendous variability of object shapes and surmount reconstruction artifacts. However, the requirement to extract valid object boundary elements and reconstruct them into a coherent and consistent anatomical structure makes the development of accurate algorithms challenging. Many methods were employed for segmentation. On one hand, deformable models [1, 2, 3, 4] have being proposed as powerful approach to reconstruct objects by exploiting constraints derived from the image data. They are defined as curves or surfaces that can move within an image domain under the influence of forces: an internal force to ensure the geometric continuity of the model, and an external force to control the closeness of models to the data. However, due to high computational complexity, they reveal poor convergence to concave boundaries and require manual interaction to initialize the model. Other common issues that need to be addressed are: the decision when to stop moving the deformable model. On other hand, the watershed transformation has proven to be a very useful and powerful tool for morphological image segmentation. The intuitive idea underlying this method is quite simple. A grayscale image considered as a topographic relief: when a landscape is immersed from pierced holes (local minima). Different basins will fill up with water. Where water coming from different basins would meet, dams are built (watershed). One of the difficulties with this concept is that it does not allow incorporation of a priori information as energy-based methods. Consequently, there is no control of the smoothness of the segmentation result. In this paper we show how to combine watershed method with a deformable simplex meshes to reconstruct 3D medical object. This leads to an efficient segmentation method integrating the strengths of watershed segmentation and deformable simplex mesh.

The remainder of this paper is organized as follows: In the section 2, we review the concepts of deformable simplex mesh. The section 3, focus on problem statement. In section 4, we present our approach to reconstruct the valid object boundaries. The emphasis will be on properties and the rules used to build our combinatorial approach. Then, section (5 and 6) provide results, summarize the proposed method and points out our future research.

2. Simplex meshes

Simplex meshes propose an original surface representation to recover 3D object boundaries. They are closely related and dual to triangulation meshes. The main geometric of three-dimensional simplex mesh consists of a simple representation by giving the position of a vertex relatively to its three neighbors. The mesh closeness to modeled object depends on the number of its vertices, the distance of vertices to the data and the relative location of vertices on the surface object

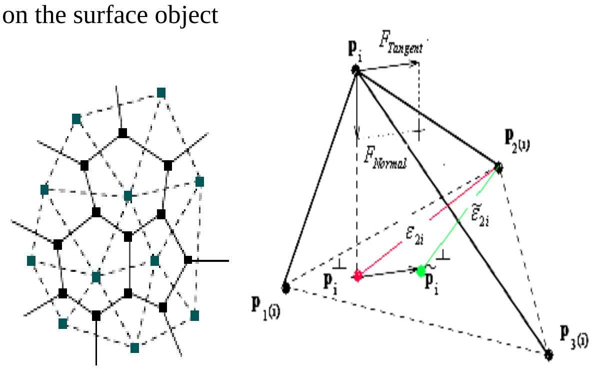

Fig.1: (Right) Duality between triangulations and simplex meshes; (Left) the geometry and definition of regularizing force.

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A deformable simplex meshes deforms under the combined action of a regularization (or internal) term and a data (or external) term enforcing the attraction of the surface towards the apparent structure boundary in the image. In order to compute the evolution of the simplex mesh, the Newtonian law is discretized using central finite differences with an explicit scheme [6]:

$$P_i^{t+1} = P_i^t + (1-\gamma)\left(P_i^t - P_i^{t-1}\right) + \alpha_i F_{\text{int}} + \beta_i F_{ext}$$

The internal force applied on vertex P_i is decomposed into a Normal force and a Tangential force [6]. The goal of the tangential force is to control the vertex position with respect to its three neighbors in the tangent plane.

$$F_{Tangent} = (\tilde{\varepsilon}_{1(i)} - \varepsilon_{1(i)})P_{1(i)} + (\tilde{\varepsilon}_2 - \varepsilon_2)P_{2(i)} + (\tilde{\varepsilon}_3 - \varepsilon_3)P_{3(i)}$$

The metric parameters $(\varepsilon_{1i}\ ;\varepsilon_{2i}\ ;\varepsilon_{3i})$ at a vertex P_i are the barycentric coordinates of $P_i^{\perp}$ which is the orthogonal projection of P_i onto the neighboring triangle $(P_{N_{1(i)}};P_{N_{2(i)}};P_{N_{3(i)}})$. The metric parameters $(\tilde{\varepsilon}_{1(i)}\ ;\tilde{\varepsilon}_{2(i)}\ ;\tilde{\varepsilon}_{3(i)})$ corresponding to the prescribed value of P_i after the deformation. The goal of the normal force is to constrain the mean curvature of the surface through the simplex angle φ_i. The general expression of F_{Normal} is governed by the reference simplex angle $\tilde{\varphi}_i$ [6]:

$$F_{Normal} = (L(r_i, d_i, \tilde{\varphi}_i) - L(r_i, d_i, \varphi_i))n_i$$

where L is the function that controls the local mean curvature at P_i.

The expression of the external force F_{ext} is dependent on the nature of the dataset. On volumetric images, the gradient intensity is used for local deflection of the mesh towards the voxels of maximum variation of intensity. The edge information, on the other hand, corresponds to gradient maxima and entails larger deformations of the mesh. Generally, the gradient intensity and edge information are combined to compute external force [5]:

$$F_{ext} = F_{Grad} + F_{Edge}$$

The Gradient force at vertex $P_{(i)}$ relies on the search in his neighbourhood for the voxel of maximum gradient intensity. If V is the voxel containing $P_{(i)}$, then we inspect around V for the voxel G_i of highest gradient intensity in a widows [m * m * m].

$$F_{Grad} = \beta_i^{Grad}\left(\left(G_i - P_i\right).n_i\right)n_i$$

The computation of the edge force at vertex $P_{(i)}$ consists in finding the closest edge voxel E_i in the normal direction n_i of the mesh. The maximum number of edge voxels scanned is determined as a percentage of the overall radius of the edge image.

$$F_{Edge} = \beta_i^{Edge}\left(E_i - P_i\right)$$

3. Problem statement

The combination of simplex meshes model with watershed segmentation provides an explicit way to compute smooth minimal surfaces. The watershed transform is the method of choice for image segmentation [9, 13, 15]. It was originally proposed by Digabel and Lantuéjoul [10] and later improved by Beucher and Lantuéjoul [8]. Many sequential algorithms have been developed to compute watershed transforms for digital images [12, 14]. They can be divided into two classes, one based on a recursive algorithm by Vincent & Soille [15], and another based on distance functions by Meyer [11]. One of the difficulties with some algorithms is that the result depends on the order in which pixels are treated during execution. Also, there are many issues concerning the accuracy of watershed lines and over-segmentation [7, 12].
The main advantages of simplex meshes are:

(i) Their geometry enables to define at each vertex discrete geometric quantities and provide a reliable solution to interpolate messing data between slices
(ii) Can be refined, adapted and represent surfaces of all topologies
(iii) The level of smoothness can be controlled.

The limits of deformable simplex meshes are:

(i) Require that objects of interest have been previously isolated from other objects
(ii) Rely on an initialization algorithm that is limited to only three different topologies
(iii) The resulted object depends on the process of segmentation and interpolation.

Indeed, one of the difficulties with internal forces formulation is that he process of deformation is based on a constant connectivity between vertices which implies that the deformation of a vertex is affected by the position of the neighboring vertices. Because the coordinates of P_i are computed relatively to its neighbors:

$$P_i = \varepsilon_{1i} P_{N_{1(i)}} + \varepsilon_{2i} P_{N_{2(i)}} + \varepsilon_{3i} P_{N_{3(i)}} + L(r_i, d_i, \varphi_i) n_i$$

Consequently, those interactions can push a number of vertices to left valid positions that conveniently fit the object boundaries in a given time and converge to the wrong position. Repeating the computation process for each vertex increases the likelihood of the invalid missing data interpolation.

Our basic assumption, the combination of simplex meshes model with watershed, is that the surface to be computed is embedded in the watershed segmentation images. This proposition is motivated by two observations. Firstly, the watershed lines contain all major boundaries of real images which can alleviate the convergence and initialization problem. Secondly, simplex meshes model is able to overcome the watershed over-segmentation and smoothness problem and can interpolate messing data between slices. Thus, we propose to solve the following combinatorial problem: finding a surface composed of a finite union of watershed lines such that the simplex meshes model minimizes a given geometric functional.

4. Our reconstruction system

In this paper, we propose a tow stages reconstruction system. In the first stage, we try to address factors that influence the evolution of deformable simplex meshes in two-dimensional space. We use the watershed transform to reduce sensitivity to initialization and alleviate the problem of convergence. In the second stage, boundaries extracted with watershed are used to generate meaningful constraints deformation rules and new guidelines to improve outcomes and decision making of simplex meshes model and other related work.

In this framework, each image is considered as a planar surface separated from the previous and next layer by a constant distance. The method consists in the first phase to segment each image. Once a set of slices has been segmented with watershed, it becomes necessary to map the result to tri-dimensional space (Lattice of watershed voxels). Watershed lattice serves to initialize in the preliminary stage the simplex meshes. The initial mesh undergoes rigid and affine transformations that place the mesh as accurately as possible over the watershed lines. After this step, the mesh begins to progressively undergo globally-constrained deformations, which allow it to adapt itself to smaller variations in the watershed lines. The mesh deformation over watershed lattice of voxels is concretely different to the deformation process in the original reconstruction algorithm of simplex meshes [10].

4.1 External forces computation

In our case, we chose to compute the external force at a vertex P_i as a vector directed along the vertex normal n_i and proportional to the distance between the current vertex position and the position of a watershed voxel. The collinearity of F_{ext} with n_i is important for two reasons [6]. First, it entails smooth deformations with attraction forces varying smoothly along the mesh. Second, the normal direction of the external force ensures the resulting mesh shape will be smooth even in the presence of sparse data and where tangential displacements could create vertices with negative metric parameters or even a self-intersecting mesh. To search watershed voxel W_i along the vertex normal direction, a line-scanning algorithm, based on an extension of the Bresenham [16] drawing line, determines the set of voxels that are visited along the normal direction. The maximum number of voxels scanned is determined as a percentage of the overall radius of the watershed image size or may be computed as a fraction of the structure size when it is known.

$$F_{ext} = (W_i - P_i)$$

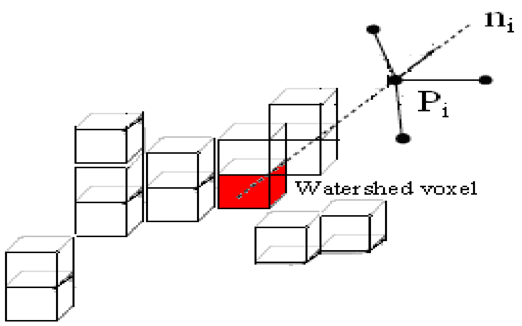


Fig.2: A line-scanning algorithm for watershed voxel along the vertex normal direction

4.2 The decision when to stop moving the deformable vertices

After the first stage of deformation, the vertices P_i of simplex mesh are thus joining the watershed voxels W_j $/ j \in \{1 .... N\}$.

The vertices that match watershed voxels are labelled with the same index $j \in \{1 \ldots N\}$:

$$\begin{cases} if \quad (W_j \neq P_i) \rightarrow P_i^{t+1} = P_i^t + (1-\gamma)(P_i^t - P_i^{t-1}) \\ \quad + \ \alpha_i F_{\text{int}} + \beta_i F_{ext} \\ if \quad (W_j = P_i) \rightarrow P_i^{t+1} = P_i^t = P_j \end{cases}$$

Consequently, unlabelled vertices follow the same law of motion. Labelled vertices P_j on simplex meshes are not deformable yet outside the watershed boundary. Indeed, this is one of the main raisons why we combine the simplex meshes model with watershed : to address the unsmoothed boundary of watershed and to avoid that the interactions between mesh vertices that push some vertices to left valid positions witch conveniently fit the object boundaries in a given time t and converge to wrong position. Unlabelled vertices attached to labelled ones deform with a different expression of the internal force.

The normal tangent force for unlabelled vertices P_i :

$$F_{Tangent} = (\tilde{\varepsilon}_{1(i)} - \varepsilon_{1(i)})P_{1(i)} + (\tilde{\varepsilon}_2 - \varepsilon_2)P_{2(i)} + (\tilde{\varepsilon}_3 - \varepsilon_3)P_{3(i)}$$

The normal tangent force for unlabelled vertices P_i attached to labelled ones P_j :

$$F_{Tangent} = (\tilde{\varepsilon}_1 - \varepsilon_1)\omega_1 + (\tilde{\varepsilon}_2 - \varepsilon_2)\omega_2 + (\tilde{\varepsilon}_3 - \varepsilon_3)\omega_3$$

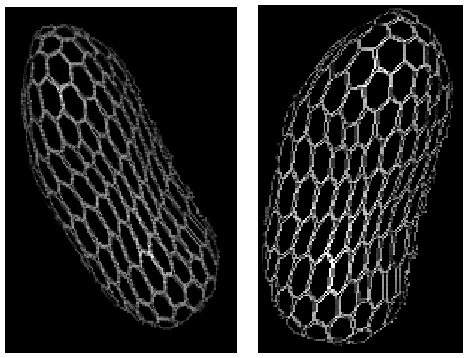
with

$$\begin{cases} if \ \ \omega_k = P_{K(i)} \quad / k \in \{1,2,3\} \rightarrow \\ \quad (\tilde{\varepsilon}_k - \varepsilon_k)\omega_K = (\tilde{\varepsilon}_{K(i)} - \varepsilon_{K(i)})P_{K(i)} \\ if \ \ \omega_k = P_{K(j)} \quad / k \in \{1,2,3\} \rightarrow \\ \quad (\tilde{\varepsilon}_k - \varepsilon_k)\omega_K = 0 \end{cases}$$

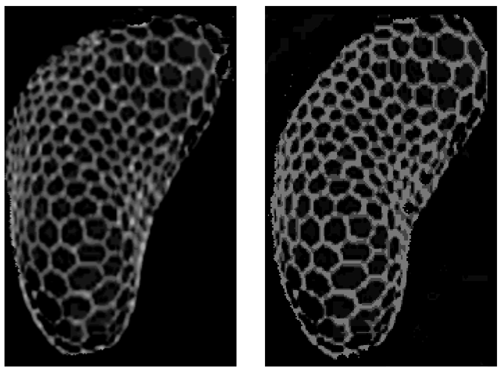
The deformable reconstruction system uses refinement of the underlying mesh structure to maintain the resolution required to accurately represent the image data during the growth of the model. A good strategy to represent an object with enough details is to concentrate vertices towards parts of high curvature in order to optimize the shape description.

5. Results

The method proposed through our system is consistent and regular. The combined results are given in figure 3. This result can be compared to that in [17], which aimed to segment a mouse kidney with simplex mesh. As observed in the results, our method has two advantages. The first one is the ability to impose constrains on the deformable simplex mesh which prevents the formation of wrong boundary and alleviate the convergence problem. The second important advantage: this approach allows an automatic initialization of the model close to the object of interest. This initialization is based on the knowledge acquired with watershed segmentation, which is often practical when segmenting complex 3D objects.



(a) (b)



(e) (f)

Fig.3: Mouse kidney segmentation: initialization of the simplex mesh in the proximity of the Lattice of watershed voxels (a, b); rigid and affine transformations and globally-constrained deformations of the mesh (e); final segmentation result (f).

6. Conclusion

We have illustrated the various properties of deformable simplex meshes to initialization and poor convergence to concave boundaries. Efficient knowledge extracted by watershed from 2D images is used to generate meaningful constraints deformation rules and to write a new internal an external force guidelines to improve outcomes of simplex meshes model. Watershed increases the likelihood to fit the valid boundaries and optimise the valid missing data interpolation. By incorporating watershed knowledge as prior information about the object shape, our proposed system combines the benefits of deformable simplex meshes for medical volume reconstruction and the robustness of the coherent and consistent watershed based methods. Our technique is generic enough to be applicable to other 3D deformable model.

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