Computerized Medical Imaging and Graphics 38 (2014) 490–507

Contents lists available at ScienceDirect

Computerized Medical Imaging and Graphics

journal homepage: www.elsevier.com/locate/compmedimag

An effective and robust method for modeling multi-furcation liver vessel by using Gap Border Pairing

Bin Fang[a,*], Nanchang Zhong[a,b], Yi Wang[a], Yuan Yan Tang[a,c], Shenhai Zheng[a], Zekun Li[a], Dong Jia-hong[d], Zhang Shao-xiang[b]

[a] College of Computer Science, Chongqing University, Chongqing 400044, PR China
[b] Department of Anatomy, The Third Military Medical University, Chongqing, Chongqing 400038, PR China
[c] Department of Computer and Information Science, The University of Macao, Macao 999078, PR China
[d] Hospital & Institute of Hepatobiliary Surgery, Chinese PLA General Hospital, Beijing 100853, PR China

ARTICLE INFO

Article history:
Received 5 July 2013
Received in revised form 23 May 2014
Accepted 27 June 2014

Keywords:
Tree-like skeleton
Multi-furcation part
Gap border pairing
Surface topology
Vessel model

ABSTRACT

Shape-based 3D surface reconstructing methods for liver vessels have difficulties to tackle with limited contrast of medical images and the intrinsic complexity of multi-furcation parts. In this paper, we propose an effective and robust technique, called Gap Border Pairing (GBPa), to reconstruct surface of liver vessels with complicated multi-furcations. The proposed method starts from a tree-like skeleton which is extracted from segmented liver vessel volumes and preprocessed as a number of simplified smooth branching lines. Secondly, for each center point of any branching line, an optimized elliptic cross-section ring (contour) is generated by optimizedly fitting its actual cross-section outline based on its tangent vector. Thirdly, a tubular surface mesh is generated for each branching line by weaving all of its adjacent rings. Then for every multi-furcation part, a transitional regular mesh is effectively and regularly reconstructed by using GBP. An initial model is generated after reconstructing all multi-furcation parts. Finally, the model is refined by using just one time subdivision and its topologies can be re-maintained by grouping its facets according to the skeleton, providing high-level editability. Our method can be automatically implemented in parallel if the segmented vessel volume and corresponding skeletons are provided. The experimental results show that GBP model is accurate enough in terms of the boundary deviations between segmented volume and the model.

1. Introductions

3D surface models of blood vessels in human organs like cerebra, livers, hearts and wombs play a significant role in medical applications [1,2]. These models provide therapy planning, virtual surgery, radiotherapy and anatomy teaching with great conveniences. In clinical applications for example, intuitive geometric representations such as vessel topologies, spatial locations of branching segments, sizes of tubes, as well as relationships between vessels and other tissues can be directly visualized in these models. Thus a good understanding of blood vessels can be provided for surgeons before surgery procedures, minimizing subjective factors which could cause erroneous assessments. As to medical teaching, novices can easily learn to master vascular anatomy by interactively manipulating these models [3], greatly shortening the time used for virtual surgery training.

The vessel volume segmented from medical images can be rendered either by volume [4] or surface [5,6], where the volume here is inferior to surface regarding the velocity and storage [7]. Therefore, surface model should still be reconstructed in the main trend of vessel visualization. As to the surface modeling, there are two main categories of methods [8]. The first category refers to shape-free techniques, which construct mesh directly from boundary voxels of vessel volume, but not make any assumption of structuralized geometry. These techniques are applied primarily for diagnosis which requires high accuracy. Marching Cubes [9] and Multi-level Partition of Unity [10] are two popular techniques on which many other shape-free methods are based. Similarly, Ding [11] introduces a region-based technique to reconstruct human airways and

Abbreviations: GBP, Gap Border Pairing; MP, main plane; EC, exclusive circle; BC, border circle; TP, turning point; BS, border segment; TT, turning triangle; $\mathbf{P}_k$, key multi-furcation point; D_a, absolute boundary deviation; D_r, relative boundary deviation.

* Corresponding author at: College of Computer Science, Chongqing University, No. 174 Shazhengjie, Shapingba, Chongqing 400044, China. Tel.: +86 13883119260.
E-mail address: fb@cqu.edu.cn (B. Fang).

http://dx.doi.org/10.1016/j.compmedimag.2014.06.020
0895-6111/

artery vessels, dividing surface mesh into tree hierarchies. But it embodies no reasonable divisions around furcating parts and no other geometric representations such as cross-section radii and tube curvatures. On contrary, the shape-based techniques, belonging to second category, are used to construct referential models for therapy planning and medicine teaching [12,13]. These techniques make assumptions that the blood vessels have strictly tree-like structures with tubular shapes. They require regular (circular or elliptic) cross-section contours and smooth organic looking shapes on non-pathological branches.

The shape-free techniques have intrinsic disadvantages. The conspicuous one is their lack of structural geometric parameters. Due to the incomplete contrasts of medical images and limited extracting methods, aliasing voxels will occur at volume boundaries, causing these techniques to generate coarse meshes. In contrast, the shape-based techniques have unparalleled advantages because they can provide high-level information such as tube trends, degrees of curvatures, cross-section radii and topological hierarchies. Though shape-based techniques have more complexities in algorithm designs, they are more advantageous than the shape-free in terms of providing anatomical information.

In usual, many methods based on shape-based techniques construct coarse meshes first by means of quads [14–16], spline curves [17] or solid NURBS mesh [18], then the coarse meshes are refined by using surface subdivision for several times. However, most existing shape-based methods have difficulties in well weaving smooth meshes around complicated multi-furcation parts, especially for liver vessels. Second, the computational overheads and storages would fall into exponential growth along with subdivision times. Third, over subdivisions would cause excessive deformations on refined models compared with segmented volumes. Forth, due to intrinsically coarse boundary voxels of segmented volume, the initial radii attached to skeleton centerlines (used by shape-based methods) generated by traditional skeletonizing methods cannot be treated as reasonable. These radii are always much smaller than their actual values, especially at narrow tubes. Finally, the centerlines are not necessarily centered at optimized center positions. All these disadvantages imply that the vessel surface meshes should be based on optimized cross-section rings (see in Section 3.1) of branching vessel tubes.

In order to solve the lacks of high-level geometric information and the disadvantages mentioned above, we introduce a novel shape-based modeling method—GBP (see Sections 4 and 5). The model by GBP is based on optimized skeletons and requires refinement with just one time subdivision. We make an assumption that the cross-section contours of vessel branches are intrinsically elliptic or circular. Firstly, the tree-like skeleton (centerlines) is extracted from the segmented vessel volume. The skeleton is composed of a number of hierarchically connecting segments which are smoothed, simplified and recombined into a number of branching lines. Second, we construct elliptic contours for every branching line by generating optimized cross-section rings for all center points of the line. Third, all adjacent rings are weaved with triangular facets to generate tubular meshes. Forth, as our key innovation, GBP is applied to construct close regular meshes for all multi-furcation parts with any numbers of branches. Finally, the initial model is refined by using one time subdivision and corresponding tree topologies are re-maintained by checking the connections between new facets and old vertices.

This article is organized as follow from Sections 2–9. Section 2 describes how to construct an adaptive tree-like skeleton from original vessel volume segmented from CT images. More detailed materials will be introduced in the experimental section (Section 7). Section 3 introduces the construction of optimized elliptic tubular surfaces for branching lines. Section 4 introduces the fundamental of GBP algorithm in 2D diagrams. Section 5 illustrates how to use GBP to reconstruct real 3D multi-furcation parts. Section 6 describes the refinement for initial GBP model and re-topologization for the model. Section 7 describes the experiments and validations. Section 8 is discussion about GBP modeling. Section 9 summaries the whole thesis and prospects our future work. The flowchart of our work is shown as Fig. 1.

2. Constructing an adaptive tree-like vessel skeleton

2.1. Segmenting the vessel volume

Since our method is shape-based, the skeletal representation for vessels is required. The scalar field of vessel volume is first segmented by using the adaptive multi-scale segmenting method introduced in our previous work [19]. There are three reasons for using this method: the incomplete contrasts between vessel patterns and backgrounds, the limited existing segmenting algorithms which cannot extract vessel volumes completely, and algorithm automaticity.

Note that the histograms of vessel backgrounds in CT images have been proved to comply with Gaussian distribution [19]. The distribution function is obtained from vessel signals segmented from backgrounds by using local optimized thresholds. Then Hessian matrix is employed to enhance the thin blood vessels before segmenting. By combining the major vessels and thin vessels via filtering, the liver vessels can be approximately completely segmented.

2.2. Extracting and preprocessing the skeleton

The tree-like vessel skeleton is extracted from scalar field of the vessel volume aforementioned. Suppose that we have an initial skeleton which is composed of a number of centerline segments connecting to each other at furcating points. A segment is single-voxel-width and represented as a sequence of continuous center points between two endpoints (furcating points or leaf points). Every center point is attached with an initial radius (local maximum boundary distance) indicating the size of the cross section at that point. One segment is set as root ranking level 0. Others are descendant segments having the ranking levels respectively equal to their depths from root segment.

However, the initial centerline segments are in general aliasing, which would cause difficulties in reconstructing cross-section rings and result in overlaps between adjacent rings. In addition, not all center points are necessary for representing the skeleton. Therefore, three steps are employed to optimize the skeleton:

(1) *Fine smoothing segments:* Interpolation methods like Hermite require values and derivatives at endpoints and are sensitive to tangents of endpoints. Gaussian smoothing must be carefully applied to different coarse centerline segments otherwise it will cause excessive deviations. By comparison, Catmull-Rom Spline is advantageously an alternative to fit centerlines under the premise in accuracy and preventing deformability. The spline is represented as Eq. (1).

$$B(\boldsymbol{u}) = \boldsymbol{u}^T \boldsymbol{M} \boldsymbol{o} \quad (1)$$

where $\boldsymbol{u}$ is the parameter vector, $\boldsymbol{M}$ is the coefficient matrix and $\boldsymbol{o}$ is the geometric information of control points. We iteratively select four sequential center points as control points, and there are two continuous center points unused between each two adjacent control points. After fitting a curve between the two middle control points, we select two equal-interval points ($\boldsymbol{u}$ = (0.33, 0.66)) on the curve to replace two corresponding unused points. Fig. 2(a) shows a centerline segment with sequential adjacent points, where $\boldsymbol{P}_0$, $\boldsymbol{P}_1$,