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Watertight modeling and segmentation of bifurcated Coronary arteries for blood flow simulation using CT imaging

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ABSTRACT

Image-based simulation of blood flow using computational fluid dynamics has been shown to play an important role in the diagnosis of ischemic coronary artery disease. Accurate extraction of complex coronary artery structures in a watertight geometry is a prerequisite, but manual segmentation is both tedious and subjective. Several semi- and fully automated coronary artery extraction approaches have been developed but have faced several challenges. Conventional voxel-based methods allow for watertight segmentation but are slow and difficult to incorporate expert knowledge. Machine learning based methods are relatively fast and capture rich information embedded in manual annotations. Although sufficient for visualization and analysis of coronary anatomy, these methods cannot be used directly for blood flow simulation if the coronary vasculature is represented as a loose combination of tubular structures and the bifurcation geometry is improperly modeled. In this paper, we propose a novel method to extract branching coronary arteries from CT imaging with a focus on explicit bifurcation modeling and application of machine learning. A bifurcation lumen is firstly modeled by generating the convex hull to join tubular vessel branches. Guided by the pre-determined centerline, machine learning based segmentation is performed to adapt the bifurcation lumen model to target vessel boundaries and smoothed by subdivision surfaces. Our experiments show the constructed coronary artery geometry from CT imaging is accurate by comparing results against the manually annotated ground-truths, and can be directly applied to coronary blood flow simulation.

1. Introduction

Coronary artery disease (CAD) is the leading cause of death in the world. In the Unites States alone, it affects more than 13 million people. CAD is a result of the buildup of cholesterol and fatty deposits—a condition called atherosclerosis—which may gradually develop into plaques on the inner wall of the coronary arteries and cause the anatomic narrowing (stenosis) or even total occlusion of the coronary arteries. Coronary artery stenosis becomes ischemic when it severely restricts the blood flow to the myocardial tissue and ultimately leads to myocardial infarction if the tissue is permanently damaged. Coronary computed tomography angiography (CTA) has emerged as a noninvasive and accurate tool for visualizing or excluding coronary artery stenosis. However, stenosis detected by coronary CTA has a poor correlation with downstream myocardial ischemia due to the unreliable mapping between anatomic narrowing and physiologic reduction of blood flow to the myocardium. Recently, computational fluid dynamics (CFD) applied to coronary CTA now allows for noninvasive calculation of coronary flow and pressure without additional medication or imaging (Kim et al., 2010) and has been shown to be effective in determination of whether a particular stenosis causes ischemia. A watertight geometric model of coronary arteries segmented from CTA images is a prerequisite to perform patient-specific CFD analysis of blood flow (Holzapfel et al., 2014; Taylor et al., 2013). The modeling procedure should ideally be fully-automated to reduce burden, improve reproducibility, and decrease the analysis time over the manual analysis.

Two main coronary arteries branch off the aorta at the ostia. The right coronary artery supplies blood mainly to the right side of the heart. The left coronary artery, which branches into the left anterior descending artery and the circumflex artery, supplies blood to the left side of the heart. The arteries further branch into smaller vessels and collectively form complex and bifurcated tree structures. Therefore, it is very challenging to extract in a single step from CTA images. The current methods to segment and model coronary arteries typically involve the following two steps: the first step is centerline detection and using the detected centerline as a guide (Schaap et al., 2009); the second step is coronary lumen segmentation (Kirişli et al., 2013).

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The centerline detection methods start with either heuristics-based (Metz et al., 2009; Gülsün and Tek, 2008) or learning-based (Zheng et al., 2011) vessel enhancement filtering. The vessels in the enhanced images become more salient than those in the original images and will ease the subsequent vessel tracing steps. By assuming vessels as a set of tubes, heuristics-based approaches are effective in highlighting tubular structures but tend to weaken the arteries at the bifurcations. In contrast, learning-based methods do not assume the vessel shape as a priori, but make use of the geometric and information embedded in manual annotations, which are more desirable in detection of both the tubular and bifurcated structures. Based on the enhanced image, Yang et al., 2012 proposed a data-driven centerline tracing method. Zheng et al., 2013 demonstrated a more robust method to trace main trunks of the coronary arteries by using a prior shape model.

Conventional voxel-based coronary lumen segmentation methods are useful for the delineation of vascular geometry and generation of watertight models by applying marching cubes (Lorensen and Cline, 1987) or level set (Sethian, 1999). A number of voxel-based methods have been proposed – for example, Antiga et al., 2003 generated patient-specific vessel meshes for CFD analysis by using level set. Wang et al., 2012 integrated the level set method in a framework by iteratively refining centerlines and detecting vessel boundaries using level-sets. They demonstrated that the iterative process was able to converge and yield high quality meshes. One drawback of Wang's method is the starting and ending points of each centerline must be fixed, which makes the segmentation relies heavily on initial centerline input and is inconvenient for manual editing. Another work by Shahzad et al.,2013 segmented lumen by combining graph cuts and kernel regression in order to accurately detect stenosis. Several open source libraries were developed, such as VMTK (Vascular Modeling Toolkit, 2016) and TubeTK (Aylward and Pace, 2010), which provide API functions for implementing level set and some vessel segmentation researches were done based on them or some commercial software (Morlacchi et al., 2013; Cárdenes et al., 2011; Mortier et al., 2010). To improve accuracy and reduce the mesh density, De Santis et al., 2011 proposed to use hexahedral meshes. The above voxel-based methods are capable of handling bifurcation geometry and construct seamless model; however, they are relatively slow and unable to incorporate expert knowledge, which limits the performance when compared to manually labeled ground truths.

On the other hand, machine learning-based methods have been proposed for the segmentation of cardiac structures with the advantages of not only increasing the segmentation speed but also learning from manual annotations. For instance, Lugauer et al.,2014 used the probabilistic boosting tree (PBT) to detect vessel lumen boundary by training the PBT classifier from manually labeled ground truths. They assumed vessels to be cylindrical objects and detected vessel boundaries along radial rays sampled uniformly from the centerline. Although tubular vessel segmentation results were satisfactory, the method did not account for the bifurcation geometry. A requirement to apply the machine learning methods to vessel segmentation is the construction of a base mesh as an initial template for subsequent adaptation to real vessel boundaries on CTA images. The base mesh must be watertight in order for the final mesh to be the same and suitable for the subsequent CFD analysis. It is straightforward to model the base mesh for individual vessel segments by tubes along centerlines with varying lumen radii; however, it is difficult to generate base meshes for bifurcations robustly, because of the large variability among the number, the size and angle of the connecting branches. Therefore, to our knowledge, most previous learning-based methods assumed a loose combination of tubular structures and did not seamlessly model the bifurcation geometry (Zheng et al., 2011; Zheng et al., 2013).

Bifurcation mesh generation from given tubular vessel models is the key to construct the watertight model of the coronary artery tree and eventually perform CFD analysis. Auricchio et al., 2014 proposed a method to generate the bifurcation mesh by first obtaining the interfaces between each branches; and then decoupling branches by these interfaces and modeling each branch as a tubular object. Another work proposed by Antiga deeply studied the geometrical relationship of the branches at bifurcations. Based on this, they sub-divided a bifurcation into four parts – three branches and one triangular-based prism and proposed a method to stitch the surface of each branch (Antiga et al., 2002). This type of methods are efficient for generating the bifurcation model with three branches, but are difficult to handle more branches. In this paper, we propose a novel method for the construction of a watertight vascular tree with a focus on explicit modeling of the bifurcations with arbitrary number of branches using learning-based segmentation. Our approach is comprised of the following four steps to construct both the centerline and lumen of the bifurcations from CTA images: (1) By using the Frangi filter (Frangi et al., 1998) and a thinning algorithm (Gonzalez, 2009), the centerlines are detected and obtain the rough locations of bifurcations. For each bifurcation, we obtain the sphere of minimum radius enclosing the bifurcation, and the vessel end-faces on the sphere surface; (2) The bifurcation centerlines (inside the sphere) are further refined using learning-based boundary detection; (3) The base bifurcation mesh is modeled by using convex hulls to join extruded tubular structures through the detected vessel end-faces. The base mesh is then subdivided to increase the resolution of editable points; (4) Guided by the obtained bifurcation centerline, we use a boosting-based classifier to adapt the convex hull points to target vessel boundaries.

This paper is organized as follows: Section 2 briefly introduces our tubular vessel modeling method. Section 3 is the main part of this paper, which introduces the bifurcation modeling steps in detail. Section 4 demonstrates the experimental results and Section 5 discusses our method and draws the conclusion.

2. Structured coronary mesh generation

Centerlines are widely used to represent the path and connectivity of blood vessels including coronary arteries (Lesage et al., 2009). In order to characterize the geometry of the lumen boundary, structured meshes are modeled by combining diameters or cross sectional areas with centerlines for the detection of narrowing or stenosis. On the other hand, unstructured meshes (e.g. Fig. 1(a)) are also used to model vessel surfaces, especially for detailed modeling of vascular shape and for generating the fluid domain for computer simulations. Both approaches have limitations considering the tubular and complex shape of blood vessels. Centerlines with diameter information are inadequate to model vessels with asymmetric or noncircular cross sections. Although unstructured meshes are excellent for representation of complex surface details, it is challenging to handle queries for global topology and connectivity.

By combining both representations, we propose to model coronary arteries by linking centerlines with structured surface meshes, as shown in Fig. 1(b). In the procedure of our system, the centerlines are firstly extracted from CT imaging by using the Frangi filter (Frangi et al., 1998) and a thinning algorithm (Gonzalez, 2009). By resampling a given centerline (dense in our case), a list of uniformly distributed nodes is generated as centerline nodes, $c_1, \ldots, c_l$, and a smoother centerline is obtained by finding a spline curve interpolating them. We define a local coordinate frame $[t,u,v]$ at each node c using a rotation minimization technique, where t is along the tangent direction of the centerline and $[u,v]$ spans a 2D plane on the cross-section. The lumen surface is modeled as a structured mesh