Implicit vessel surface reconstruction for visualization and CFD simulation

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Abstract

Objective: Accurate and high-quality reconstructions of vascular structures are essential for vascular disease diagnosis and blood flow simulations. These applications necessitate a trade-off between accuracy and smoothness. An additional requirement for the volume grid generation for Computational Fluid Dynamics (CFD) simulations is a high triangle quality. We propose a method that produces an accurate reconstruction of the vessel surface with satisfactory surface quality.

Methods: A point cloud representing the vascular boundary is generated based on a segmentation result. Thin vessels are subsampled to enable an accurate reconstruction. A signed distance field is generated using Multi-level Partition of Unity Implicits and subsequently polygonized using a surface tracking approach. To guarantee a high triangle quality, the surface is remeshed.

Results: Compared to other methods, our approach represents a good trade-off between accuracy and smoothness. For the tested data, the average surface deviation to the segmentation results is 0.19 voxel diagonals and the maximum equi-angle skewness values are below 0.75.

Conclusions: The generated surfaces are considerably more accurate than those obtained using model-based approaches. Compared to other model-free approaches, the proposed method produces smoother results and thus better supports the perception and interpretation of the vascular topology. Moreover, the triangle quality of the generated surfaces is suitable for CFD simulations.

Keywords Vessel visualization · Surface reconstruction · Blood flow simulation · CFD simulation

Introduction

The reconstruction of vascular structures deserves special attention since vascular trees are among the most complex structures of the human body. An accurate and high-quality reconstruction is essential for applications in the field of diagnosis and blood flow simulation [1]. In diagnosis of vascular diseases, the local evaluation of the vessel cross section is essential to detect and characterize narrowings, such as a stenosis as well as widenings, e.g. an aneurysm. A high quality in terms of surface smoothness is important to avoid distortions caused by surface artifacts.

Furthermore, a high surface quality as well as high reconstruction accuracy is crucial for Computational Fluid Dynamics (CFD) to guarantee correct simulation results and to avoid numerical instabilities. Simulations of the blood flow enable the study of hemodynamic characteristics such as intra-aneurysmal flow patterns or the wall shear stress. The results could be used to decide if an aneurysm has to be treated by coiling or stenting. We do not discuss issues such as Non-Newtonian characteristics of blood flow, elastic behavior of the vessel wall or the appropriateness of laminar flow conditions. These issues are discussed, e.g. in [1]. Instead we focus on general properties of grids in the preprocessing for blood flow simulations. An additional important prerequisite for a CFD simulation is a high triangle quality in terms of edge ratio. Thin and elongated triangles may cause numerical instabilities and need to be avoided. Moreover, the triangle size should...
not change abruptly. A higher resolution in areas with high curvature is desirable, however smooth transitions in triangle quality are required.

Model-based vessel visualization techniques are well established in the field of therapy planning. The reconstruction is based on model assumptions, in particular a circular cross-section is often assumed. A high surface quality can be achieved by explicitly fitting graphics primitives to the centerline, (see, e.g. [2] where truncated cones are employed) or by using implicit representations (see, e.g. [3] where Convolution Surfaces are employed, see Fig. 14 b). However, the accuracy of the reconstruction is not sufficient for diagnosis and blood flow simulation. Pathologic structures cannot be captured correctly using circular cross sections since the morphology of such structures is highly irregular and does not exhibit a rotational symmetric shape (see Fig. 1). In addition, the cross section of the vessel lumen might deviate from a circle (shaped like an ellipse or even like an “8”) depending on the transmural blood pressure. A blood flow computation based on inaccurate surfaces generates misleading results.

A higher accuracy can be achieved using model-free approaches like Marching Cubes [4]. In principle, those algorithms can be applied directly to the image data and generate a surface based on a threshold. However, this is problematic in the case of vascular structures. Due to image noise and inhomogeneities in the contrast agent distribution this does not always lead to accurate results, in particular for MRI data. Furthermore, small structures might be suppressed depending on the chosen threshold. Hence vascular structures need to be explicitly segmented (e.g. with level sets or snakes) in most cases before a surface can be reconstructed. A subsequent application of a model-free method suffers from strong aliasing artifacts like staircases which might hamper the visual interpretation of the vessel surface and therefore complicate the diagnosis. Furthermore, staircase artifacts are very problematic for CFD simulations since they might lead to numerical problems. Common approaches to smooth these artifacts in the segmentation mask or in extracted surface meshes especially of filigree vascular structures mostly remove relevant detail and yield reduced accuracy [5]. Volume-preserving smoothing approaches like Constrained Elastic Surface Nets constrain the displacement of the vertices to prevent shrinkage [6]. However, even those methods fail to preserve small structures like thin vessels. An up to date overview of vessel visualization techniques can be found in [7].

Method

Pipeline overview

The proposed reconstruction pipeline is summarized in Fig. 2. The input for the pipeline is binary segmented image data that contains vascular structures. In the first step of our pipeline, a point cloud is generated that represents the boundary between the segmented vessel and the background. We developed an adaptive point cloud generation algorithm that allows the faithful reconstruction of small vessels. To generate a signed distance field based on this point cloud, we apply the Multi-level Partition of Unity Implicits (MPU Implicits) algorithm that was developed by Ohtake et al. [8]. The polygonization algorithm of Jules Bloomenthal is used to generate a polygonization of this function [9]. The result can directly be used for visualization.

To this point, the pipeline is similar to the method described by Braude et al. [10] but targeted at the appropriate representation of vascular structures. The major difference is the adaptive point cloud generation algorithm that strongly differs from the one proposed by Braude et al. In addition we derived rules for the estimation of appropriate parameter values for the generation and polygonization of the MPU Implicits to ease and speed up the application of our method.

To allow the utilization of the generated surfaces in the context of CFD simulation, we add additional post-processing steps. For mesh quality improvement we apply edge collapsing and edge flipping as described in [11]. A reduction of triangles is yielded by using the Advancing Front remeshing algorithm of Schreiner et al. [12]. The result of the post processing can also be used for visualization. This is especially reasonable for the visualization of the simulation results on the surface.

Point cloud extraction

The point cloud extraction algorithm is aimed at the reconstruction of small structures like thin vessels. It is driven by the voxel grid of the segmentation result. However, to prevent aliasing artifacts, point positions are not strictly aligned to voxel centers but distributed in the volume of the voxels. We use those background voxels, that are closest to the given object voxels, as the basis of point placement. We refer to those voxels as outer boundary voxels. Based on the 3D-6-neighborhood $nb(v)$ of an outer boundary voxel $v$,