Graphical Models 74 (2012) 109–120

Contents lists available at SciVerse ScienceDirect

Graphical Models

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

Robust curve skeleton extraction for vascular structures ☆

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ARTICLE INFO

Article history:
Received 7 March 2012
Accepted 28 March 2012
Available online 12 April 2012

Keywords:
Skeleton extraction
Skeleton growing
Mesh processing
Vascular structures

ABSTRACT

Extracting curve skeletons for vascular structures is vital for many medical applications. However, most of existing curve skeleton extraction methods are either too complicated or not robust to be applied directly on vascular meshes. In this paper, we present a simple and robust three-step approach for one-dimensional curve skeleton extraction for vascular models. Firstly, the given vascular mesh is iteratively contracted until it is thin enough. Then the contracted mesh is further subdivided. Thereafter our approach proceeds over the point cloud domain yielded by the vertices of the subdivided mesh. Secondly, the joint and branch points of the model are detected. Finally, a skeleton growing procedure is proposed to generate the curve skeleton. Experimental results show that our approach is robust for vascular structures of any topology, e.g. with or without loops or with nearby structures. Additional experiments demonstrate that our approach can be extended to handle other common shapes.

1. Introduction

Curve skeletons are compact representations of three-dimensional (3D) objects. Since they capture significant geometric and topological information of original objects, curve skeletons are practical in computer graphics and visualization. Simple and robust curve skeleton extraction methods have been the research focus for many years. A lot of algorithms for extracting curve skeletons of 3D objects have been proposed in recent decades [11].

Curve skeleton extractions of vascular models represented as surface meshes are also fundamental problems with many medical applications such as flight-path planning in virtual endoscopy, vascular segmentation, vascular hierarchy labeling. Unfortunately, the previous approaches for extracting curve skeletons from volume data require transforming the surface mesh representations of original models to volumetric representations, which is prone to errors. Most of the curve skeleton extraction methods for meshes are designed to deal with a variety of shapes for a wider applicability. Although some of them generate excellent results, they are too complicated either in the processing procedure or in the data structures they employed. As we focus on vascular meshes, the existing curve skeleton extraction algorithms for point clouds cannot be directly applied on our vascular models.

In this paper, an automatic method which is simple and robust aiming at vascular meshes is proposed. The algorithm utilizes the mesh contraction method proposed by Au et al. [4] to get a visually thin contracted mesh. This smoothing procedure does not alter the topology of the original mesh. Instead of using the modified mesh simplification methods in [4] to construct the curve skeleton, the presented approach employs an adaptive feature-preserving subdivision strategy on the contracted mesh to increase its local vertex density and converts the vertices of the subdivided mesh to a thin point cloud. Then the curve skeleton is constructed from the thin point cloud.

☆ This paper has been recommended for acceptance by Jarek Rossignac.

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http://dx.doi.org/10.1016/j.gmod.2012.03.008

An essential step for curve skeleton extraction from point clouds is to correctly detect joints and branches of objects. An effective detection scheme using principal component analysis (PCA) and point clustering is introduced to distinguish them. Then a skeleton growing approach, which is similar to the seeded region growing algorithm in image analysis, is proposed. The initial skeleton seeds are constructed by a simple joint handling procedure. Finally, the algorithm begins the skeleton growing procedure with the initial skeleton seeds to construct the one-dimensional (1D) curve skeleton. This procedure is based on an improved directional curve growing procedure [18]. Every initial skeleton seed has its own growing direction. For each growing direction, the curve skeleton stops growing whenever there are no points ahead or the current growing direction meets another initial skeleton seed. The complete 1D curve skeleton is constructed when all the growing directions stop growing.

Compared with previous methods, our approach has two advantages:

1. Our approach is simple. Most of existing mesh skeleton extraction methods based on a simple contraction procedure are always followed by a mesh simplification procedure. Besides maintaining the information of the complex topology, the user has to add other constraints to control the simplification procedure carefully in order to achieve better results. On the other hand, in the point cloud domain, the point cloud contraction is much more difficult and complex than mesh contraction while the following processing is relatively simple. Our method takes advantage of the mesh contraction idea to obtain a thin point cloud and utilizes the simple curve reconstruction algorithms for point clouds to construct the curve skeleton.
2. Our approach is automatic and robust for vascular structures with complex topology. After detection of the joint and branch points, an automatic joint clustering and initial skeleton seeds construction algorithm is applied on the point cloud without any user interaction. The skeleton growing algorithm is devised to handle models with any topology. In contrast to traditional curve construction methods, the proposed skeleton growing algorithm cannot only robustly process vascular structures with loops, but also works well for vascular structures with high local curvature or branches that are very close.

In the following section, related works for this paper is described. In Section 3, we outline details of our algorithm. Experimental results and discussion are presented in Section 4. Conclusions and comments on future work are included in Section 5.

2. Related work

As curve skeletons of 3D objects do not have a strict definition, a great number of curve skeleton extraction methods for different types of data and different applications have been proposed. We categorize the main representations of the current 3D objects into three groups: volumetric representations, surface mesh representations and point cloud representations. In the following paragraphs we review only some of the representative methods for each representation form. For the rest, we refer the reader to the recent comprehensive survey of Cornea et al. [11].

For volume data, voxel-thinning methods [15,34] produce curve skeletons by iteratively deleting the object boundary voxels that satisfy certain topological and geometric constraints. Ma and Sonka [21] introduced a fully parallel thinning algorithm to extract skeletons of the input models. The deleting templates they used are grouped in four classes. If the neighborhood configuration of an voxel which is nontail matches at least one deleting template in the four classes, the algorithm deletes the voxel in parallel. Later in [22], they described another thinning algorithm that divides the discrete space into four subfields. At each sub-iteration the voxels belonging to one of the subfields are considered for deletion. They also proposed an approach to simplify the proof procedure of verifying the topological soundness of a 3D thinning algorithm. Palágyi and Kuba [25] introduced an efficient parallel thinning algorithm. Each iteration deletion step is composed of 12 subiterations each of which can be executed in parallel. They demonstrate a possible way for constructing nonconventional directional thinning algorithms. Sadleir and Whelan [28,29] proposed an optimized topology thinning algorithm based on Look-up-table (LUT). The algorithm greatly improves the efficiency of the traditional thinning algorithm. Bouix et al. [8] described a centerline extraction method by thinning the medial surface of objects. The medial surface is computed by thresholding the negative average outward flux of the gradient field of the distance map. However, medial surface is sensitive to small changes in the object's boundary caused by the way it is defined [3], which makes the final curve skeletons also sensitive to small changes in the object's boundary. Ding et al. [14] extended the LUT-based topology thinning method. They introduced a minimum heap to get the voxel nearest to the boundary. By employing a region growing procedure, the method avoids the global connectivity test and gets rid of the redundant ring generated by the thinning algorithm.

Distance-filed methods based on distance transformation firstly calculate the minimum distance to the boundary for internal voxels to get a distance field. Then a search procedure is applied through the distance field to find ridge voxels. The non-ridge voxels are removed, leaving the ridge voxels as candidate voxels for curve skeletons. A pruning and connection step are followed to construct the complete curve skeletons from the candidate voxels. Zhou et al. [38] and Zhou and Toga [39] introduced a voxel coding approach that combines the distance-from-source (DFS) field with the general distance-from-boundary (DFB) field to generate the candidate voxels. The local maximum paths are employed to connect the skeleton voxels. Wan et al. [36] described a generic algorithm that firstly converts the volumetric DFB field into a 3D directed weighted graph and then a minimum-cost spanning tree is built from the weighted graph to construct the skeletons. Bitter et al. [6,7] proposed a method that also combines the DFS and DFB field but the searching of candidate voxels is based on gradient in the new distance field. The voxels