Vascular Models: From Raw Data to Geometric Models

Allen R. Sanderson[1, 2], Elaine Cohen[2], Thomas C. Henderson[2] and Dennis L. Parker[1]

1. Department of Radiology, The University of Utah, Salt Lake City, Utah 84132, U.S.A.
2. Department of Computer Science, The University of Utah, Salt Lake City, Utah 84112, U.S.A.

Introduction

In the areas of MR and X-ray vascular imaging, it is becoming increasingly important for researchers and clinicians to have computer analysis tools available not only for data visualization but also for extracting quantitative information. This information includes geometrical and physical characteristics which can be used in both a research and clinical setting. Although there has been a significant effort to improve visualization techniques such as maximum intensity projection [1], [2], very little progress had been made beyond making diametrical measurements and tracking vessels in 2-D and 3-D angiograms [3], [4].

In this paper we present a technique to generate accurate computer models of the vascular system directly from multi-modality image data. When fully validated, the models will make it possible to analyze the vascular system more completely. For example, computer models can be used for monitoring vessel sizes in pre- and post-operative studies, or can serve as the basis for performing complex fluid flow analysis. Furthermore, incorporating physical properties such as the vessel elasticity into the models would allow for their use in a surgical planning environment. In creating the computer models, we have developed a multi-step process incorporating several techniques commonly found in many other computer vision problems. The process includes four steps: segmentation, thinning, directed graph formation, and surface construction. In this paper each of these techniques and their details are presented.

Segmentation

As with most computer vision problems the segmentation step is the most critical and often the most sensitive step. Although both X-ray and MR angiography produce high contrast images, they can have a large deviation in the gray scale range. This large range makes it difficult to segment images with simple thresholding techniques. Researchers using binary or hysteresis thresholding have reported two problems: segmenting undesirable features which must later be removed and the absence important features which were below the threshold [4], [7].

Previously, we reported on a technique for simultaneously segmenting registered MR and X-ray angiograms using a region growing technique coupled with an adaptive threshold [5]. A region growing technique is particularly appropriate for segmenting strongly connected structures such as the vascular system. When combined with an adaptive threshold it is possible to segment features which might otherwise be missed using simpler techniques. Others have reported using a similar technique with good success [6].

Thinning 3-D Binary Data

Thinning or skeletonization is the process of reducing an object into a “stick-figure” or skeleton. Most techniques form a skeleton by iteratively removing (thinning) points from the boundary while usually, but not always, preserving path and surface continuity between regions. The skeleton of an object can be described in terms of a medial axis transform and/or a central axis. Blum’s Medial Axis Transform [8] was one of the earliest algorithms reported that produced a skeleton. Direct implementation of Blum’s definition leads to several problems, the most notable being the formation of disconnected skeletons even when the original object is connected. However, it does have the advantage that the object can be easily reconstructed, since a radius is associated with each point on the axis. A less restrictive description of a skeleton is the central axis, which is concerned with maintaining only topology and connectivity.

In this particular research, we are interested in topology as a source for directing the type of parametric surfaces that will be used to approximate the data. As such, we have directed our research effects towards thinning algorithms which produce a central axis. For example, [9], [10] and [11] describe 3D thinning algorithms based on local connectivity and topology, and iteratively use local operators to decide whether a point may be removed from the boundary. Although connectivity and topology are used in the decision process, alone they do not guarantee that a skeleton will be produced. In fact, if used alone, objects of genus zero would be reduced to a single point. Thus, each algorithm uses end conditions to control the thinning. As previously mentioned, it is possible to obtain a medial or central axis using many different thinning algorithms. For example, in [9] and [11] a central axis was obtained using the criteria that if a voxel had only one neighbor (8 or 26 connected) it could not be thinned. This condition causes other voxels not to be thinned, because doing so would break the connectivity. More complicated criteria can lead to a medial axis.

In [11], Tsao and Fu present an algorithm for 3-D thinning using local transforms to first find the medial surface, which is then thinned into a skeleton. The local transform used by Tsao and Fu and described in [10], checks the surface connectivity before and after the possible removal of a voxel. If the connectivity remains the same then the voxel may be removed. However, this is a necessary but not sufficient condition and is discussed in [12]. Thus, it is also necessary to check the object connectivity before removing a voxel, since it is possible to preserve the surface connectivity while dividing the object into two parts. Hafford and Preston [9] note that Tsao and Fu's algorithm can be simplified by using eight subfields rather than the six primary directions (north, south, east, west, and up, down) as subfields in conjunction with 3 checking planes. By using the full eight subfields, the thinning algorithm can be based on 26-neighbor thinning instead of only 6-neighbor thinning. This improvement also allows for the thinning of medial surfaces that are not oriented along one of the 3 checking planes.

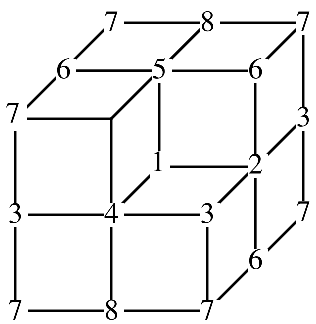

Figure 1. Cube with eight sub-fields.

Using the requirements of maintaining both topology and connectivity, we have extended Tsao and Fu's pseudo-parallel thinning algorithm to use a total of 8 subfields while maintaining both surface and object connectivity.

When thinning noisy binary data it is useful to smooth the data first. Without smoothing the data first, thinning algorithms tend to produce many spurious axes ("twigs") which complicate the graph formation process. To improve the quality of the thinning process, we have developed a "steerable" filter which uses local axis of inertia in conjunction with a bi-symmetrical 3D Gaussian function [13]. The filter has been tuned to smooth 3D tree like structures without growing the branches together.

A second part of the thinning process consists of approximating the vessel's shape along its centerline. If the thinning process produces a skeleton which is assumed to be the centerline of the vessel, and if the vessel is assumed to be circular, then a simple distance transform can be used to approximate the radius. In actuality, vessels are not round but have more of an elliptical shape.

It is possible to approximate the vessel's radius by examining a cross-section that is tangent to the vessel's centerline. Since the cross-section is planar, a simple 2D Euclidean distance transform can be used. We have chosen the distance between the vessel skeleton and the closest point in the vessel which lies on the boundary to approximate the vessel radius. This approximation will almost always provide too small of a radius but it is satisfactory for describing the low frequency features of the vessel.

Graph Formation

Although the results of the thinning process are not graphs themselves, they are very close to being graphs. All that remains is to identify the end and branch points which become nodes in the graph. The topology of the object is known once a graph is formed, and so, it is possible to select the correct surface representation needed to approximate the data.

A simple method of converting the skeleton into a graph is to track the skeleton voxel by voxel [14]. During the tracking, each voxel is identified as being either an end, a normal, or a branch point. An end point is identified by having only one connected neighbor while a normal point has two neighbors. Any points with more than two neighbors are labeled as branch points. This technique relies on having a one voxel thick skeleton and is easily used on 2D or 3D data. The tracking is implicitly defined as a depth-first search and, as such, cycles are found during the tracking. A method of identifying such points as part of the thinning process is described in [15]. This technique has several advantages over the described method, but the final pass on the data must insure that there is one-to-one correspondence in the graph, (i.e. the results of the thinning process must be one voxel wide, and a bifurcation node must have no more than three neighbors).

Surface Construction

Currently, researchers have been limited to parametrically describing the vascular system using the centerlines defined by the skeletonization process with the radius approximated by the distance transform [4]. This information can be used to form contiguous surfaces out of a series of piecewise cylinders (C^0 at joints). However, such a representation creates surfaces with a very irregular and almost bumpy texture. Further, the use of this model is limited to processes such as visualization and can not be easily used in performing fluid flow analysis studies which require a hollow and smooth surface. To increase the robustness of such intermediate results we have chosen to use B-spline surfaces for our final representation. B-spline surfaces are highly advantageous since they can be used to smoothly represent complex shapes with a minimum number of parameters.

By using B-spline surfaces we are able to significantly reduce the amount of data that must be stored (at a small reduction in precision), while increasing our ability to visualize and extract quantitative information from the data. However, the vascular system is composed of at least two unique local topologies: the vessel body and the vessel bifurcation, each requiring different B-spline surface models. We have successfully developed two B-spline template models which can be used to describe any part of the vascular structure using a minimum number of parameters which join with C^1 continuity. Although we rely upon having a centerline and radius data to initially describe the vessel shape, we are able to reduce the amount of data needed once we convert the centerlines into B-spline curves, this subsequently reduces the amount of data needed to describe the vessel structure.

Results

We have applied the region growing algorithm to segment a sub-set of an MR angiogram, as shown in Figure 2 and Figure 3. We have applied the thinning and graph formation algorithm to the segmented data as shown in Figure 4. The results clearly show that the thinning is able to produce approximate centerlines to the vasculature and that this information is sufficient to form a graph to direct the surface construction process. Although the segmentation algorithm is able to extract small vessels (<2.0mm), it is still very sensitive to data with large deviations in contrast. This sensitivity and inability to fully smooth the segmented data results in small vascular structures ("twigs") that must be removed before the graph formation step. Although smoothing using a steerable filter helps, it does not completely remove the possibility of forming spurious vascular structures.

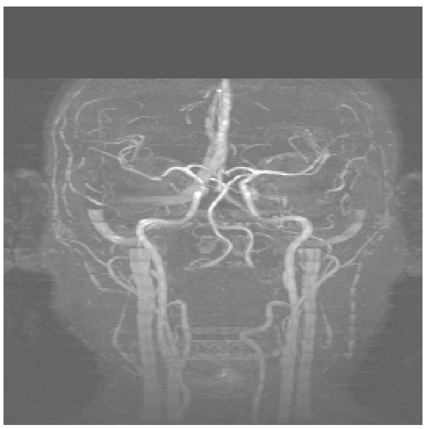

Figure 2. MOSTA MR Angiogram 256x256x212

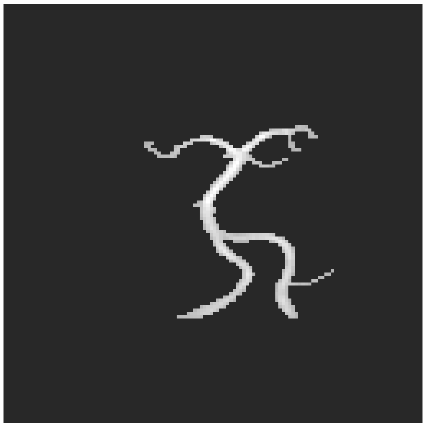

Figure 3. 3D segmented subset of original data.

Figure 4. Thinned 3D data with node points.

The two surface template models were easily adapted to the many geometries found in the vascular system using two parameters, the vessel position and local radii, which were used to describe the initial B-spline surfaces. After a data reduction step, we were able to achieve approximately a 2:1 data reduction without significantly affecting the results. The final result is shown in Figure 5 and Figure 6.

Conclusion

We have successfully demonstrated the ability to extract and describe vascular structures in angiograms in the form of a directed graph. In conjunction with centerline and radii information, this graph is used to form a completely parametric representation using B-spline surfaces of the vascular system. This has not been previously demonstrated. The results of this work can be used as the basis for visualizing and monitoring changes

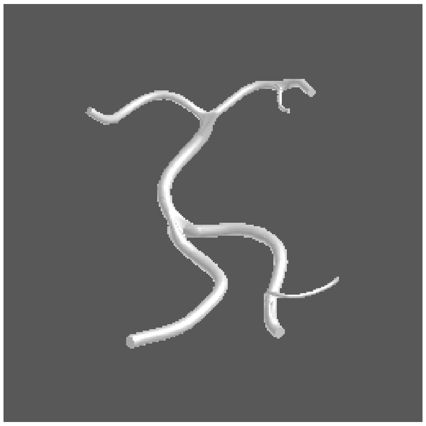

Figure 5. 3D B-spline surface rendering.

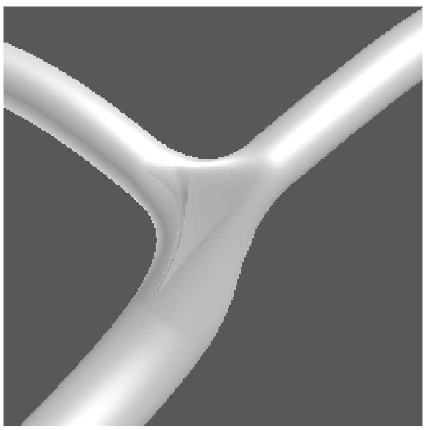

Figure 6. 3D B-spline bifurcation rendering.

in the vascular structure, for performing complex fluid flow analyses, or as a tool in such areas as stereotactic surgery.

There are still several areas of active research which must be considered. For instance, the current B-spline surfaces are only able to represent low frequency structures and therefore only serve as an approximation. A comparison of the parametric bifurcations must be made against real anatomy. Future work would include using these surfaces as a basis to recover high frequency structures such as stenosis and aneurysms which are of greater importance to clinicians and researchers.

Acknowledgments

This work was supported in part by the NSF (CDA-9024721, DARPA (N00014-92-J-4113), the NSF and DARPA Science and Technology Center for Computer Graphics, and Scientific Visualization (ASC-89-20219), the NIH (RO1 HL48223). All opinions, findings, conclusions or recommendations expressed in this document are those of the authors and do not necessarily reflect the views of the sponsoring agencies.

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