VASCULAR TREE CHARACTERISTIC TABLE BUILDING FROM 3D MR BRAIN ANGIOGRAPHY IMAGES

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Abstract. Analysis of 3D brain angiography images implemented in this paper consists of several steps: (1) segmentation to extract the vascular tree; (2) cavity deletion to fill possible 3D holes inside the vasculature; (3) skeletonization to extract the central line of the vascular network; (4) characteristic table building, including raster to vector conversion and length, area and volume computation. This approach produces the characteristic table of the vasculature. The description includes length, cross section area and volume measurements of the tree. The table also stores the topology structure of the tree, so that the vasculature can be restored. The result is saved in XML file. The paper describes all these steps in details.

1. Introduction

Modern MR scanners can produce three-dimensional (3D) brain images of enormous size. Manual methods of processing such images are very time consuming and require hours of painstaking and laborious work. A typical vascular tree consists of hundreds branches and many bifurcations. Studying vasculature permits to answer on basic physiologic questions. Knowledge of principal laws of governing the branching geometry and fluid transport mechanisms allows detecting different diseases in the very beginning. Complexity, size and spatial structure of the tree make it impractical to use purely manual methods of image processing.

A similar work was done in [5]. The authors proposed a technique for display laryngo-tracheal tract caliber changes and quantification of stenotic segments regarding site, degree and length. This technique is based on Spiral-CT data processing. The approach allows computing length and cross section area measurements and studying cross section area profile using GUI tools. However, laryngo-tracheal tract is a vessel object without any bifurcations. In difference to the vasculature, the tract is not a tree, and in the best case the approach described will allow to obtain only one pathway through the tree from aorta to terminal arteries. Besides, this method needs some interactive control during the process: the operator has to mark the start and the end points of the central path.

Another approach proposed in [2] presents three applications which allow assessing the laryngotracheal stenosis, infrarenal aortic aneurysms and colons by computing cross-sectional profiles and displaying them as line charts. The proposed process is sketched as follows: semiautomatic snake-based segmentation, morphological filtering, curve thinning, raster-to-vector conversion, pruning, smoothing and cross-sectional profile calculation. The approach in [6] uses almost the same scheme.

The goal of this paper is to present the technique of building characteristic table of vascular tree with a topology structure, cross section area and volume measurements using fast and memory efficient algorithms. The whole process is divided into four steps (see Fig.1):

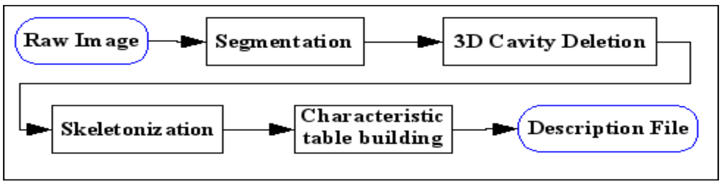


Fig. 1. Image processing procedure.

1.Image segmentation using 3D seeded region growing algorithm;
2. 3D cavity deletion using 2D region growing algorithm and morphological closing;
3. Image skeletonization by 3D thinning algorithm;
4. Characteristic table filling;

In order to extract the vascular tree from a MR brain angiography image a segmentation process is executed. Seeded region growing algorithm considers not only the image intensity distribution, but also the spatial relationships (connectivity) of voxels constituting the regions of interests. The method is memory-efficient and the greatest advantage is its ability to extract large complex trees.

The result of segmentation can contain erroneous interior tree cavities, which should be filled. Such cavities alter the tree digital topology. In order to produce a solid tree a 3D cavity deletion process is performed. Firstly, a 2D region growing algorithm is applied for each slice of the image. It fills possible 2D holes inside objects. Since the algorithm uses data structures previously build at the segmentation step, it enables very fast and memory-efficient one-pass processing. Finally, a 3D morphological closing is applied to make the surface of the vascular object smoother.

The previous procedure results in a solid vascular tree. In order to define the skeleton (central axes) of this network a 3D thinning iterative algorithm is performed. The advantage of this method is that it preserves the topology, is memory efficient and quite simple in realization.

As far as the tree and its skeleton are obtained, they are stored in the same image volume. However, the tree storage demands excessive space, since typically about 90% of image voxels belong to the background, which does not provide any information about tree geometry and quantitative characteristics.

In order to fill the characteristic table with tree descriptions a raster to vector conversion is performed. During the conversion process cross-section areas are computed for each skeleton point as well as volume for all tree branches. All results are also saved into a characteristic table. Let us note that in difference of other approaches, our cross-section area and volume computation procedure is based on cubic spline interpolation.

2. Segmentation

Our goal is to extract the vascular tree. MR brain angiography images have some common characteristics. First, the vascular tree appears brighter than does the background. Second, voxels at the middle of the large proximal vessels may appear dimmer than do the other tree voxels. Third, intensity values along the tree may vary. Finally, the image is very large. Therefore the segmentation algorithm should be memory efficient and should take into consideration not only image intensity distribution, but also the spatial connectivity of voxels constituting the vasculature.

The segmentation algorithm used is proposed in [7]. The essential property of 3D seeded region-growing algorithm is that it does not depend on initial point position; it is memory efficient and considers spatial connectivity of tree voxels. Besides, it is fast – it enables a two-scan procedure to extract the complete vasculature and to save it.

The algorithm includes two main steps: 2D region growing on the individual slices and region merging between consecutive slices to form complete regions. For each 2D slice, the method starts with a set of seeds that meet certain restrictive criteria. These seeded regions grow then recursively including neighbors that satisfy loosened criteria until no further neighbors are added. The method uses a region table and an equivalence table. The region table stores the information on individual grown regions like a region ID, its bounding-box, number of seeds, and number of points. The equivalence table contains composite information on 3D regions after merging. Each entry of the equivalence table maintains a list of region IDs of equivalent regions and other data obtained from the region table. At the end of the growing and merging processes, the equivalence table is taken as the final region table.

Because the processing of 3D image requires only one pass through 2D slices, the visited slices are no longer used and the voxels on them can store their region numbers. Therefore, 3D seeded region growing requires only one copy of the image, plus a small working buffer to maintain the region and equivalence tables. See results of segmentation in Figure 2.

Before processing some parameters should be predefined. The include criteria for acceptable regions of interest and how to grow the regions: the intensity range for valid seeds, allowed intensity for voxels in the final region, tolerance level and search-neighborhood size. These parameters can be defined manually or generated automatically. A special algorithm was developed to determine these values. The method is based on the property of voxels of vascular tree in MR images to have the highest intensity level among others image objects. The second property is that the ratio of amount of seed voxels to the total amount of background voxels in the image is a relatively constant value. The parameters may be estimated from this ratio and from the position of the second main peak on the histogram. So the image histogram is used for analysis of voxel intensity distribution in the image (Fig. 3).

The additional advantage of the proposed approach is that it allows coloring separate vascular tree components in different colors, which can be useful for further processing.

(a) *(b)* *(c)*

Fig. 2. Segmentation results. (a) slice of 3D MRI data; (b) zoomed data shown in red rectangle of (a); (c) corresponding result of region growing algorithm – vascular tree points.

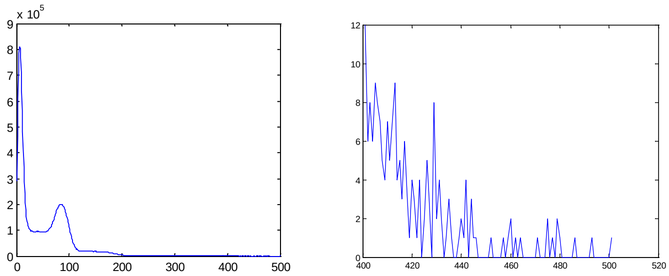


Fig. 3. Histogram of 3D MR image. Left picture shows the histogram for the whole intensity range. Right picture shows the intensity distribution for the interval [401, 501].

3. Cavity Deletion

Three-dimensional cavity deletion is applied to fill possible erroneous interior tree cavities contained in the segmented result. This happens because voxels in the middle of large proximal vessels may appear dimmer than the other tree voxels and intensity values along the tree may vary. The skeletonization process is very sensitive to such artifacts. 3D holes inside the vasculature may cause creation of incorrect topological structures.

(a) *(b)* *(c)*

Fig. 4. Example of cavity deletion processing: (a) after segmentation; (b) after 2D hole filling; (c) after 3D closing.

A special algorithm is performed to get rid of cavities. This procedure is very fast and memory efficient. It takes only one scan processing. Besides, only one image slice plus a small buffer are loaded during the computation. The method uses the region table data structure created at the previous step. The main idea is to check for each image slice all 2D regions registered in the region table and to fill holes inside these regions. Since the algorithm fills all 2D holes in all slices, 3D holes inside the vasculature disappear.

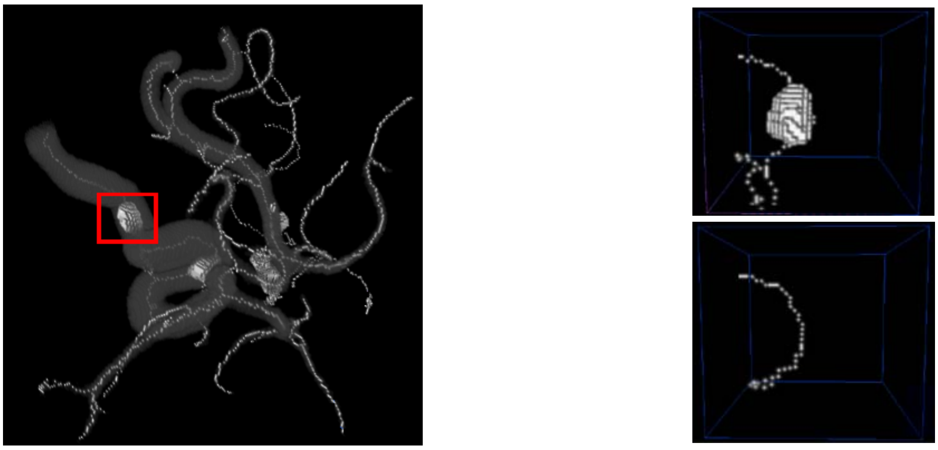
The following algorithm can be performed after or instead of the above described hole filling approach. To make the surface of the vascular object smoother the morphological 3D closing is applied. The closing operation fills 3D holes of a certain size inside objects. Therefore, one can use the operation instead of the 2D hole filling procedure. To make the closing operation faster, several improvements are used. The structuring element used has a cubic shape and it is decomposed into three orthogonal line element parallel to x, y and z directions. The size of a structuring element is a parameter. The erosion and dilation operations defining the closing are performed slice by slice. In order to reduce the amount of neighborhood checking, for z-line direction the nearest point map is applied. For a current slice the map stores the position of the nearest image point. The map is updated for every slice during the operation procedure for x and y line directions.

At the end of the cavity deletion step the image contains a solid vascular network. This step is not time consuming, because it takes one image scan to fill 2D holes plus two image scans to do the closing operation. Let us mention that the algorithm works even with several separate objects of different colors.

4. Skeletonization

The notation of skeleton was introduced by Blum [1] as a region-based shape descriptor which characterizes the general form of objects/shapes. The thinning process is a frequently used method for producing an approximation to the skeleton in a topology-preserving way. To extract skeleton of vascular tree, a 6-subiterational thinning algorithm is applied. We apply the algorithm proposed by Palagyi and Kuba [3].

The iterative thinning algorithm deletes border points that satisfy certain conditions. The process is repeated until there are no more simple points to be changed. A simple point is a point, whose deletion does not alter the object topology. Deletion criteria are defined as a set of templates or matching masks. If 26 neighbors in a 3x3x3 grid match any of templates of this set, than the current border point has to be deleted (to belong to the background). Each iteration consists of six subiterations. Each subiteration corresponds to a certain direction of verification. Totally there are six directions: Up – Down, Down – Up, North – South, South – North, East – West and West – East. During the subiteration, the procedure checks all image voxels. Every direction has its own set of templates. Since every voxel has 26 neighbors in a cubic grid belonging either to the object or background, then there are 2^{26} (= 67108864) possible different combinations.



(a) *(b)*

Fig. 5. (a) Vascular tree obtained with the skeleton inside. The skeleton has artifacts because the cavity deletion procedure was not performed; (b) The upper picture shows a segment of the skeleton shown in red rectangle of (a). The lower picture shows a part this segment when the cavity deletion procedure was previously applied to the vascular tree.

Several improvements were introduced to make the algorithm more efficient. Look Up-Table (LUT) was applied to store decisions for all neighborhood combinations. LUT allows obtaining a decision for any voxel in a constant time: one has to create a LUT input index based on the values of 26 voxel neighbors and to get the decision from the table. This approach significantly reduces the number of operations during the iteration process. LUT is built in advance, it does not depend on input images and it is a part of the algorithm. An additional algorithm is developed to fill in the LUT efficiently. Slice management is realized in our implementation of the skeletonization algorithm. It is useful for elongated objects, whose radius varies significantly. Slice management allows processing those slices only, for which the skeletonization was not completed. It reduces the number of iterations in the algorithm.

Let us note that the thinning algorithm is very sensitive to artifacts in the image. Therefore, it is important to perform the cavity deletion procedure (see Fig. 5).

5. Characteristic table building

Graph representation of the vascular network is more compact and more suitable for further studying. That is why a raster to vector conversion is performed. The result of this conversion is a forest consisting of trees. A branch of a tree is a segment either between two consequent bifurcations or between a bifurcation and end point. For each branch the following characteristics are computed: length, cross section areas and volume. The length is defined by the number of skeleton points the branch consists of. In [2,4] the cross section area is computed in the plane orthogonal to the central path. In this paper we use spline interpolation of skeleton as in [4]. Each spline segment is built by four control points. Cross-section area is computed in the plane orthogonal to the tangent vector at the current point. Besides, in the same plane we compute the cross-section centroid. It is used together with the tangent vector and the cross section area for computing the branch volume as it was proposed in [4]. Results of computation are saved into a file in XML format.

6. Results

This paper describes a pipeline implemented for computing a characteristic table of vascular tree from 3D MR angiography images. This pipeline works either in a fully automatic manner or supports some interaction while defining input parameters. The pipeline consists of segmentation, cavity deletion, skeletonization and characteristic table building steps. Fast and memory efficient algorithms are implemented.

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