Vascular segmentation algorithm using locally adaptive region growing based on centerline estimation

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ABSTRACT

In this paper, we propose a new region-based approach on the basis of centerline estimation, to segment vascular networks in 3D CTA/MRA images. The proposed algorithm is applied repeatedly to newly updated local cubes. It consists of three tasks: local region growing, surfacic connected component labeling, and next local cube detection. The cube size is adaptively determined according to the estimated diameter. After region growing inside a local cube, we perform the connected component labeling procedure on all 6 faces of the current local cube (surfacic component labeling). Then the detected surfacic components are put into a queue to serve as seeds of following local cubes. Contrary to conventional centerline-tracking methods, the proposed algorithm can detect all bifurcations without any restriction because a region-based method is used at every local cube. And by confining region growing to a local cube, it can be more effective in producing prospective results. It should be noticed that the segmentation result is divided into several branches, so a user can easily edit the result branch-by-branch. The proposed method can automatically generate a flyway in a virtual angioscopic system since it provides a tree structure of the detected branches.

Keywords: Vascular segmentation, vessel tracking, centerline estimation and locally adaptable region growing.

1. INTRODUCTION

An accurate description of vessel structures in 3D medical images is very important in many clinical applications such as quantitative diagnosis, surgical planning, monitoring disease progress or remission, etc. One of the current limitations in endovascular techniques is that they rely totally on 2-D information: X-ray image projections, maximum intensity projections from MRA data, and slices from MRA and contrast-agent CT data. However, the task of the clinician involves the manipulation of objects in a complex 3-D environment. These kinds of operations in the clinical area usually require the segmentation of 3-D vessel structures.

Therefore, various approaches have been proposed to segment vessel structures from 3-D medical images, such as CT angiographic images and MR angiographic images. Some papers have proposed to use model-based methods, where vessels are treated as cylinder-like shapes using different representations such as generalized cylinders, or B-splines. But model-based methods have the inherent risk that they may not be able to detect abnormalities, for example aneurysms, even if the detection of abnormalities is more important than that of normal cases in the clinical field. In image segmentation, conventional methods based on region growing usually produce well-defined object boundaries in most cases, if the intensities inside the object of interest do not vary drastically. However, for vascular structures, which are usually composed of very long and narrow pipe-like objects, steady-going intensity variation may affect segmentation results if the parameters used for homogeneity tests in the region growing process are not adjusted adaptively.

To perform locally adaptive region growing on vascular structures, we propose a systematic scheme, in which region growing is confined to a small local cube. After region growing is done in a local cube, the next local cubes are determined. Contrary to conventional centerline-tracking methods, the proposed algorithm can detect all bifurcations without any restriction, because a region-based method is used at every local cube separately. It should be noted that the algorithm can
produce more prospective results, since we confine region growing to a local cube and make the parameters adaptive to local statistics.

In the following sections, we will explain the proposed algorithm in detail and demonstrate through computer simulation that our method can provide prospective results.

2. PROPOSED ALGORITHM

2.1 OVERALL STRUCTURE

The overall structure of the proposed algorithm is shown in Fig. 1. The iterative procedure begins from a given initial seed area and is applied repeatedly to the local cubes, which are stored in a queue at the previous steps. At each local cube, three tasks are applied successively; local region growing, surfacic component labeling, and next local cube detection. After local region growing, we look for candidate areas for the next branches by analyzing the segmentation result in the current local cube. By performing connected component labeling on 6 faces of the local cube, we can detect branches and estimate the position of the next local cubes. And each connected component on 6 faces of the local cube is regarded as a new seed area of next local cubes. Here, the size of the local cube is determined by considering the area of the corresponding surfacic component. The next local cubes detected in the current one are pushed into the queue for later processing. The iterative procedure ends when no more local cubes remain in the queue. In the following subsections, the method will be explained in detail.

2.2 LOCAL REGION GROWING

In the proposed algorithm, region growing is confined to a local cube. Starting from the seed points that are detected by surfacic component labeling in the parent local cube, neighboring points are merged through a pre-defined homogeneity test. Here, all parameters used in the homogeneity test can be estimated from statistics of the parent local cube. Notice that any locally adaptive scheme can be applied here. In this paper, after local region growing in the parent local cube, we calculate the mean intensity value $\mu$ of object voxels and find $\sigma$ such that more than 90% of object voxels exist in the intensity range of $[\mu - \sigma, \mu + \sigma]$. Then these values are stored to be used in child local cubes.
2.3 SURFACIC COMPONENT LABELING

In order to detect branches and the position of the next local cube, topological information is used after local region growing. We perform connected component labeling on 6 faces of the local cube, not inside the local cube. Since adjacent faces of the cube are regarded as being connected to each other, a connected component can span on two or three adjacent faces. Fig. 2 shows an example of the surfacic component labeling. In this example, the left one shows two connected components and the other shows three components connected.

2.4 DETECTION OF BIFURCATION

By analyzing the results from surfacic component labeling described in the previous subsection, we can detect all bifurcation in the current local cube and find the position of next local cubes. To avoid some errors caused by improper estimation of the local cube size, we examine whether all the connected components satisfy the following rule.

*Rule:* A single connected component cannot exist on both of the opposite faces of the local cube simultaneously.

Fig. 3 illustrates an example of the case that the above rule does not hold. (Fig. 3 is depicted in 2-D space for convenience.) Unless all connected components satisfy the rule above, the result from region growing is discarded and the local cube is enlarged twice in each direction to be pushed into the queue again. Otherwise, surfacic connected components are stored as seed areas for the next local cubes, respectively.

Let $C_r$ be the center position of the current local cube, $S_j$ the $j$-th surfacic connected component, and $\{p_x \in S_j\}$ the points
belonging to \( S_j \). Then, the center position of the next local cube derived from \( S_j, C_{i+1,j} \), is decided as follows.

\[
C_{i+1,j} = \alpha \cdot \frac{1}{\text{Card}(S_j)} \sum_{p_i \in S_j} (p_i - C_i) + C_i,
\]

where \( \alpha \) is a constant parameter. And the size of next local cube is determined adaptively according to the area of the corresponding connected component, \( S_j \), so that the next cube can slightly overlap the current local cube. Surface components of the local cube are stored as seed areas, each of which will be used in a later local region growing process. Fig. 4 shows two examples of the bifurcation detection procedure. Here the procedure is depicted in 2-D space for convenience.

Notice that the proposed scheme can detect all branches in any direction since it has no restriction on surface component labeling, while conventional centerline tracking methods search for next candidates on a restricted region \(^{1,2}\).

### 2.5 TREE-STRUCTURE OF THE SEGMENTATION RESULTS

In the proposed method, parent-child relationships can be traced among local cubes. Hence, we can produce a tree-like network by dividing the resulting segmentation into several branches, where a user can edit the segmentation result very easily by adopting a prune-and-graft strategy. It should also be noticed that the estimated centerline of the vessel structure can be built up in the proposed method. Therefore, by simply storing the center position of the local cubes, an automatic flyway can be generated in a virtual angiographic system.

### 3. SIMULATION RESULTS

In computer simulation, the iterative procedure of the proposed algorithm begins with a user-selected point, which is considered the seed point for the first local cube. In this paper, we try to segment three different data sets: MRA head images, MRA neck images, and CTA abdomen images. Dimensions and resolutions of the images are as shown in Table 1. Some of these images are shown in Figs. 5, 6, and 7, respectively. And user-selected initial points are marked with white arrows on the corresponding images. Figs. 8, 9, and 10 demonstrate 3-D volume rendering images using segmentation results from the proposed algorithm. From these figures, the proposed method proves to provide prospective segmentation.
results for vascular structures.

Table. 1. Dimension and resolution of the test images.

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<tr>
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<th>Dimension</th>
<th>Resolution [mm]</th>
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<tbody>
<tr>
<td>MRA head</td>
<td>512 × 512 × 136</td>
<td>0.43 × 0.43 × 0.80</td>
</tr>
<tr>
<td>MRA neck</td>
<td>256 × 256 × 130</td>
<td>0.78 × 0.78 × 1.50</td>
</tr>
<tr>
<td>CTA abdomen</td>
<td>512 × 512 × 90</td>
<td>0.59 × 0.59 × 1.50</td>
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4. CONCLUSION

As described above, region growing should be adaptable to local statistics in order to produce good segmentation of vessel structures, because steady-going intensity variation could severely affect results. In this paper, we propose a new systematic local region growing method with centerline estimation. The proposed method segments vessel structures in 3D images iteratively, starting from a user-selected point. Contrary to conventional centerline-tracking methods, the proposed method can detect all kinds of branches in any direction.

We applied the proposed method to MR angiographic images and CT angiographic images. The simulation results demonstrate that the proposed method is very suitable for segmenting tree-like structures of vessels. Notice that the segmentation results are divided into branches, so a user can edit the results branch-by-branch. Also by storing the center positions of local cubes during the process, it can generate an automatic flyway for angioscopic systems without additional computation.

5. REFERENCES

Fig. 5. Several 2D slice images from MR head angiographic image data (level: 115, width: 170).
The user-selected point is marked with a white arrow.

Fig. 6. Several 2D slice images from MR neck angiographic image data (level: 50, width: 80).
The user-selected point is marked with a white arrow.
Fig. 7. Several 2D slice images from CTA abdomen image data (level: 1140, width: 620). The user-selected point is marked with a white arrow.

Fig. 8. Segmentation results of MRA head image data.
Fig. 9. Segmentation results of MRA neck image data.

Fig. 10. Segmentation results of CTA abdomen image data.