Automatic Peripheral Vessel Tracking in 3D Contrast-enhanced MR Angiography

H. Xue[1,2], S. J. Malik[1], S. Schmitz[1], D. Oregan[1], D. Rueckert[2], and J. Hajnal[1]

[1]Robert Steiner MRI Unit Imaging Sciences Department, MRC Clinical Sciences Centre, Hammersmith Hospital, Imperial College London, London, London, United Kingdom, [2]Visual Information Processing, Department of Computing, Imperial College London, London, London, United Kingdom

Introduction Three dimensional Contrast-enhanced MR Angiography (3D CE-MRA) has become an accepted technique for vascular imaging particularly in the abdomen, thorax and extremities. This technique can provide 3D angiograms of excellent contrast and minimize flow-related artifacts. However, quantitative 3D morphological information on vessels cannot be easily obtained by simple visualization tools, such as the maximum intensity projection (MIP). We have therefore developed an automatic algorithm for extracting the 3D geometry and radius of vessels from CE-MRA images.

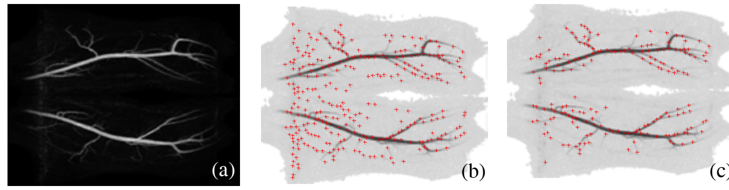

Fig. 1. Scheme of seed generation. (a) A MIP of CE-MRA image. (b) The differential-geometrical ridge detector L_{vv} is computed on the 2D MIP. After a non-maximum suppression, significant ridge points are selected (marked as red crosses). (c) Detecting the zero-crossing within the neighbor of each significant ridge point refines the output of non-maximum suppression. Points on the background are almost entirely removed and seeds left spread over the vessel tree.

Method Our approach is to find vessel centre lines by detecting and then following intensity ridges in the contrast enhanced images. A ridge traversal method originally presented in [1] is used. This starts from a seed point near the vessel centre and moves to a ridge point by minimizing a ridgeness function $J(\vec{x}) = (\vec{v}_1 \cdot \nabla I)^2 + (\vec{v}_2 \cdot \nabla I)^2 \approx 0$ where I is image intensity and $\vec{v}_1$ and $\vec{v}_2$ are normalized eigenvectors corresponding to the k-th smallest eigenvalues of the Hessian of I at $\vec{x}$. Many seeds are required for full vessel extraction and their placement is time consuming and laborious, so a key requirement for automation is to generate seeds close to vessel centers. To do this we first identify candidate vessel points in 2D MIPs (Fig. 1(a)) using a differential-geometrical ridge detector, L_{vv} [2]. At a 2D ridge point, L_{vv} has a local maximum. We compute this measurement for the 2D MIP. The result includes not only points in vessels, but also many extra points resulting from local noise in the images (Fig. 1(b)). To exclude non-vessel points we use the scalar product of the local gradient and principal curvature of intensity, which should approximate zero at a ridge point. By detecting zero-crossings within the neighborhood of each candidate point, we refine the output of 2D seeds (Fig. 1(c)). Finally, the 3D voxels corresponding to 2D seeds are used to automate the vessel detection process. To estimate vessel radius the vessel centerlines are first smoothed using approximation splines and orthogonal cross-sections are generated. From the vessel centre point in these planes rays are cast that are terminated at local intensity gradient maxima. This is taken to define the vessel border. The radius r is then computed from the area of vessel lumen approximated by polygons fitted to the ends of the rays. As vessel bifurcation points result in abrupt shape deviation in polygons, which causes errors in radius, to avoid this, the location of each ray end point is compared to a low order polynomial estimate constructed from neighboring rays. Those points with their residual larger than a threshold (0.05 in experiments) are replaced by linear interpolation of adjacent low residual points. Experiments show that radius over-estimation is effectively rectified by this adaptive strategy.

Results The method has been tested on 4 subjects. All images were acquired at a 3T MR imaging system (Philips Intera) using a 6 element sense torso coil. A Gd-DTPA contrast agent (Magnevist, Schering, Berlin, Germany) administered at 4ml/sec was applied in all cases to obtain vessel enhancement. The following imaging parameters were used: TR 4.1ms, TE 1.2ms, Flip Angle 18 degrees, scan matrix $256 \times 215 \times 55$, voxel size $1.0 \times 1.0 \times 1.0\text{mm}^3$. The extraction result from the image in Fig. 1(a) is shown in Fig. 2 which indicates typical performance of our method. We quantify the segmentation completeness (ability to extract all vessel branches), consistency (spatial distance error between different extractions) and speed (extraction speed including seed generation and ridge detection and time cost to complete the segmentation based on the automatic results) of the proposed algorithm. Specifically, the completeness is measured by the statistic $C = LA/LM$. LA is the total length of vessel tree automatically extracted. LM is the total length of the manual segmentation of the same image. The mean completeness is $93.2 \pm 1.96\%$. The precision and consistency of vessel extraction is quantified by the averaged spatial distance between the branches extracted from manual and automatic segmentations. The mean distance is 0.396 mm and its upper bound is 0.552 mm for all subjects. As for the speed of vessel extraction, the most time-consuming part is the 3D ridge detection which costs ~8mins on approximated 100 seeds on current PC hardware (Pentium 4, 3.00GHz, 3GB of RAM, Windows XP). The whole processing time approximates ~15mins, and is completely automatic. The radius estimation method has been tested on a patient with bilateral popliteal artery stenosis (Fig. 3). The estimated radius demonstrates the expected gradual decrease from root to tip. The arteries with stenosis are characterized by the low radius values. The mean relative ratios of stenosis are 8.3% and 13.0% for both sides for the patient.

Conclusion We have presented methods to automatically extract peripheral vessels from CE-MRA images. This method detects the intensity ridges to track the vessel centerline and estimates vessel radius. We quantified the segmentation completeness, consistency and speed of the proposed algorithm. The radius estimation method is evaluated on patients with stenosis. Experiment results show the effectiveness of proposed vessel extraction and radius estimation scheme.

References

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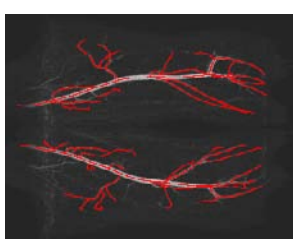

Fig. 2. Extracted vessels are overlapped on the MIP.

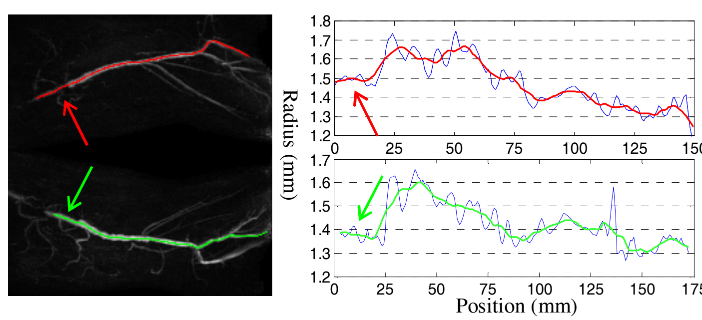

Fig. 3. A patient with bilateral popliteal artery stenosis shown by arrows was scanned and their bilateral popliteal arteries were extracted. Estimated radii of the popliteal arteries are smoothed and used to quantify stenosis.