# Generating 3D Vascular Models from MRA Images Using Dynamic Programming

B. E. Chapman[1], D. L. Parker[2], L. Zhang[3]

[1]Radiology, University of Pittsburgh, Pittsburgh, PA, United States, [2]Radiology, University of Utah, Salt Lake City, UT, United States, [3]University of Utah, Salt Lake City, UT, United States

**Introduction**

MRA images that are routinely obtained are of sufficient quality that it is feasible to consider automated quantification of important vascular features. In this presentation we present an alternative algorithm based on dynamic programming for automatically extracting vessel centerlines and using these centerlines to generate 3D vascular models. This technique accurately extracts centerlines for all vessel sizes of interest. The method is described an initial results are presented.

**Methods**

Our algorithm consists of the following steps: 0) image acquisition; 1) generation of a binary mask of the vasculature; 2) computation of a centeredness measure; 3) setting of seed points; 4) computation of cost function describing the minimal cost path from each point in the mask to the seed point(s); 5) identifying vascular endpoints; 6) tracing centerlines from endpoints to seed points; 7) recognizing bifurcations and splitting centerlines into distinct vascular segments; 8) fitting smoothing splines to the centerline segments.

**Image Acquisition:** Images were acquired on a 512x192x64 grid covering a 220x165x58 mm3 imaging volume. Central k-space MT was used to suppress background signal. Images were reconstructed with zero-filled interpolation to a 1024x768x128 matrix and subregioned to a 512x512x120 matrix centered around the Circle of Willis. **Generation of Binary Mask:** The TOF MRA imagees were first processed with a Hessian matrix based vessel enhancement filter. The filter output was then sinc-interpolated in the axial direction to generate isotropic data (512x512x240 matrix). The ZBS algorithm (Parker, JMRI 2000) was then used to generate a binary mask of the vasculature. **Centeredness Measure:** To date we have primarily restricted our centeredness measure (CM) to be functions of the Euclidean distance from edge (DFE). So that the center of the vessel has a minimal centeredness measure CM is computed as $CM = (\max(DFE) - DFE)^n$. We have examined n=0.5, 1 and 2 and have found the best results with n=2. **Setting Seed Points:** Seed points were manually set in the right and left ICA as well as the basilar artery. **Computing Cost Function:** The cost function (CF) is computed in an iterataive manner, similar to the Dijkstra algorithm (Dijkstra, Numerishe Mathematik, 1959) . The cost function of the mask is first initialized to a high value. The CF at the seed points is then set to zero. This constitutes iteration zero. For iteration n+1, the CF is propagated from each point in the mask for which the CF decreased in iteration n. CF values are propagated from point x2 to x1 according to $CF(x_2|x_1) = \alpha CM(x_2) + \beta\|x_1 - x_2\| + \gamma CF(x_1)$. That is the CF at $x_2$ is determined by CM at the point, the step distance from $x_1$ and the CF at $x_1$. The constants $\alpha$, $\beta$, $\gamma$ determine the relative weighting of each of these terms. **Vascular Endpoints:** Vascular endpoints are characterized by two properties: 1) they are local minima in CM for an N-point neighborhood, 2) they are local maxima in CF for an N-point neighborhood. **Tracing Centerlines:** To start the centerline tracing, we select the endpoint with the largest CF value. This ostensibly represents the end point the farthest from the seed point. Tracing the centerline consists of examining the 26-point neighborhood of the last point added to the centerline and adding to the centerline the neighbor with the lowest CF value. This continues until the centerline encounters a CF value of zero (initially seed points). After the centerline is completed, we take a heuristic step to facilitate convergence of centerlines; namely we reset the CF value along the points on the traced centerline to zero. We then take the remaining end-point with the largest CF value and trace it back to the first voxel with a zero value (either a seed point or a previously traced centerline). **Determining Vascular Segments:** Bifurcations are easily recognized as points of convergence of two centerlines. Traced centerlines are then broken into distinct segments defined by endpoints, seepoints and bifurcations. Because there is not complete specificity in endpoint detection, the method generates false centerlines. A simple first step solution to this problem is to prune segments shorter than a given length. The minimum segment length will necessarily be determined by the geometry of the vascular objects in the image. For our intracranial images, we have found a minimum segment length of 20 voxels to work reasonably well. **Fitting Splines:** Because of the discrete nature of the images, compounded by imperfections in the segmentation, the centerlines are not smooth. To create a smooth centerline we use a cubic least-squares spline.

**Results:**

Figure 1 shows an example vascular tree with fitted spline centerlines as well as the corresponding mapping of voxels within the segmentation to distinct vascular segments. Figure 2 shows example calculations (including vascular tortuosity) that can be made to describe the vascular morphology.

**Discussion**

We have presented an improved algorithm for automatically generating vascular models based on dynamic programming extracting of vascular centerlines. The algorithm can run in a completely automated fashion, although for these results we did manually set seed points. Improvements are still needed. First, the method is highly dependent on the quality of the vascular segmentation, a still unsolved problem. Second, a more specific method of detecting vascular endpoints is needed as pruning short segments is not entirely robust.

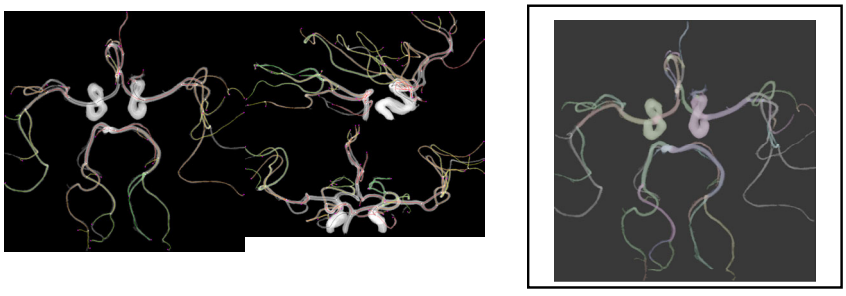

Fig. 1. (left) Fitted centerline segments. Segments are color coded for distance from seed points. Seeds were placed in each ICA and the basilar artery. (right) Voxel mappings to distinct vessel centerlines.

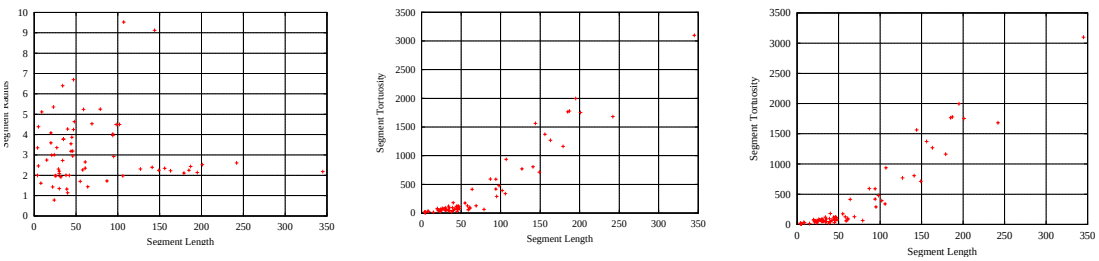


Fig. 2. Scatter plots of estimated radius vs. length (left), tortuosity vs. length (center) and tortuosity vs. radius (right). Tortuosity was defined as the sum of the centerline curvature (2nd derivative) divided by centerline length. Vessel radius was estimated from the formulae for the volume of a cylinder, with the voxel count being the volume. Units are in voxels.