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Coronary Artery Segmentation Using Geometric Moments based Tracking and Snake-Driven Refinement

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Abstract

Automatic or semi-automatic segmentation and tracking of artery trees from computed tomography angiography (CTA) is an important step to improve the diagnosis and treatment of artery diseases, but it still remains a significant challenging problem. In this paper, we present an artery extraction method to address the challenge. The proposed method consists of two steps: (1) a geometric moments based tracking to secure a rough centerline, and (2) a fully automatic generalized cylinder structure-based snake method to refine the centerlines and estimate the radii of the arteries. In this method, a new line direction based on first and second order geometric moments is adopted while both gradient and intensity information are used in the snake model to improve the accuracy. The approach has been evaluated on synthetic images as well as 8 clinical coronary CTA images with 32 coronary arteries. Our method achieves 94.7% overlap tracking ability within an average distance inside the vessel of 0.36mm.

I. Introduction

Vessel segmentation, quantification and visualization are very important tasks in the field of medical image analysis. Among these, the segmentation of vascular structures is particularly valuable for diagnosis assistance, treatment and surgery [1–4]. Till now, vascular segmentation still relies heavily on manual operations, which tend to have problems with repeatability, reproducibility and human errors. To overcome the aforementioned problems, the medical imaging community has proposed automatic approaches for vessel segmentation (see also [1–4] for detailed review).

Vascular segmentation method can be roughly grouped into three general classes: *Region growing methods* [5] incrementally segment an object by recruiting neighboring voxels from seed points or regions located inside a vessel, based on some inclusion criteria. Although popular for their simplicity and efficiency, their performance is heavily dependent on the inclusion criteria, which is especially difficult to define for complex structures. *Active contours*, including snakes [6, 7] and level set [8–10] based methods, evolve an interface through external force and internal forces. It is widely used for its flexibility of the initial position and ability to handle geometric topological changing. However, only low-level operations such as pixel-wise inclusion criteria are adopted and higher-level information are not fully utilized.

Centerline based approaches seek additional robustness by relying on higher-level information, such as the localization of the center of the vessel and the estimation of its direction [11, 12]. The Hessian matrix based vesselness enhancement [13] is the most common tool. In this approach, scale selection procedure is always needed due to the variational sizes of the vessels. Nevertheless, developing a fully robust automated method for vessel segmentation is still a challenging task due to the cluttered objects, partial volume effects, intensity inhomogeneity, complex vessel structures and huge size and high dimensionality.

In this paper, we present a novel centerline based method for vessel segmentation. The method uses a geometric moment based tracking to detect a centerline, followed by snake-driven centerline refinement and radii estimation to ensure tracking accuracy. The proposed method does not require scale selection, is more robust than conventional tracking methods, is computational efficient, and is accurate.

II. Method

A. Artery centerline tracking with geometric moment

The 3-D geometric moments of a grey-level intensity function f at location $s(x_0, y_0, z_0)$ are defined as:

$$\mathbf{M}_{pqr} = \iiint_V x^p y^q z^r f(x, y, z) dx dy dz \quad (1)$$

with $p + q + r = L$ are the order of the moments, V is a cubic window centered at $s(x_0, y_0, z_0)$. Denote $\{\mathbf{M}_{000}, \mathbf{M}_{001}, \mathbf{M}_{010}, \mathbf{M}_{100}, \mathbf{M}_{011}, \mathbf{M}_{101}, \mathbf{M}_{110}, \mathbf{M}_{200}, \mathbf{M}_{020}, \mathbf{M}_{002}\}$ as the order-2 moments, it is possible to compute the moment of the inertia matrix Φ as

$$\Phi = \begin{bmatrix} \mu_{200} & \mu_{110} & \mu_{101} \\ \mu_{110} & \mu_{020} & \mu_{011} \\ \mu_{101} & \mu_{011} & \mu_{002} \end{bmatrix} \quad (2)$$

where μ_{pqr} is defined as the central moment:

$$\mu_{pqr} = \mathbf{M}_{pqr} - \frac{\mathbf{M}_{100}^p \cdot \mathbf{M}_{010}^q \cdot \mathbf{M}_{001}^r}{\mathbf{M}_{000}} \quad (3)$$

It has been observed that the eigenvector corresponding to the largest eigenvalue of matrix Φ is indeed oriented along the cylinder principal axis. Also, it is reasonable to assume that the true center point is always on or near the center of mass. Thus, our proposed new tracking algorithm is as follows. Denote $\mathbf{u}$ as the directional vector based on order-2 geometric moment, $\mathbf{v}$ as the directional vector pointing to the center of mass (CM) and $\|\mathbf{v}\| = 1$. The local line direction vector $\mathbf{w}$ is estimated as follows:

$$\mathbf{w} = a\mathbf{u} + (1 - a)[\mathbf{v} - \mathbf{u}(\mathbf{u} \cdot \mathbf{v})] \quad (4)$$

where $\mathbf{v} - \mathbf{u}(\mathbf{u} \cdot \mathbf{v})$ means only the component of $\mathbf{v}$ that is perpendicular to $\mathbf{u}$ is used. a is a constant weight balance which is fixed at 0.5 in this work. Figure 1 illustrates how $\mathbf{w}$ is computed based on $\mathbf{u}$ and $\mathbf{v}$. By combining both order-2 geometric moment vector and the directional vector pointing to the center of mass, the advantages are not only to improve the tracking accuracy, but also to ensure that the tracking is always inside the tubular structures.

The design of the grey-level intensity function f in (1) is very important to ensure the robustness of the centerline tracking algorithm. In this work, we use a non-parametric model to design f such that the arteries can be distinguished from the surrounding tissues and bones with similar or higher intensity values. In this method, every single sample is treated as a Gaussian distribution and all these small Gaussian kernels are integrated to derive the overall non-parametric estimation of the probability density function (p.d.f.) which serves as f . Denote p_i as a point on the detected centerline, the p.d.f. of the local artery region can be expressed as follows:

$$P(i|p_i) = \frac{1}{S(R_M)} \int_{R_M} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(i-I(y))^2}{2\sigma^2}} dy \quad (5)$$

where $i = 0, \dots, 255$ denotes the pixel intensity value for an 8-bit images, R_M denotes the local region around point p_i , $S(R_M)$ denotes the area of R_M , y represents pixels in R_M and $I(y)$ denotes its intensity value. σ is a constant specifying the width of the Gaussian kernel. Based on the estimated p.d.f, each voxel is assigned a probability value, which will be served as the weight function f in the line direction estimation. In our work, σ is fixed to 4 while R_M is a region with p_i as the central point. The overall procedure for centerline tracking has five steps:

- Step 1:** manually initialize one starting point P_0 inside the beginning part and P_{end} inside the ending port of the artery region;
- Step 2:** based on the current point, establish a local region W (larger than the cubic window V) and calculate the local probability map according to (5);
- Step 3:** calculate the line direction $\mathbf{w}$ based on $\mathbf{v}$ and $\mathbf{u}$;
- Step 4:** track the next point by $p_{i+1} = p_i + r\mathbf{w}$ where r is a fixed radius parameter (fixed to 0.15 in this work);
- Step 5:** determine which one of the three conditions p_{i+1} satisfies: reaching the nearby region of p_E , then the tracking is finished; lying inside the local region W , then go to step 3 to continue the tracking; or lying outside W , then go to step 2 to continue the tracking.

During the tracking, one important criteria is that if the angle between two consecutive estimated $\mathbf{u}$ is larger than 90° ($\mathbf{u}^i \cdot \mathbf{u}^{i+1} < 0$), then the vector should be turned around as $\mathbf{u}^{i+1}$

$= -\mathbf{u}^{i+1}$. This is to ensure the consistence of the eigenvectors of the inertia matrix. Figure 2 shows the tracking procedure in a flowchart.

B. Centerline Refinement and Radius Estimation

To further segment the artery contour and improve the accuracy of centerline extraction, a generalized cylinder model based snake method is used. We assume that the images satisfy: (1) the intensity in the vessel is continuous; (2) each cross section of the vessel is similar to a circle. The structure of an artery is represented by the generalized cylinder model (GCM). The GCM is composed of two parts: a centerline $\mathbf{X} = \{\mathbf{x}_i\}$, $i = 0, 1, \dots, N$, where $\mathbf{x}_i$ represents a center point on the centerline and N is the total number of center points, and a series of circles perpendicular to the centerline. Also, an active contour model (snake) [16] is used to fit the GCM structure to the data by minimizing an energy function, which contains external and internal energies. The approach proposed in [10] utilizes two external energy terms to attract the snake to boundaries, namely, gradient-based offset-medialness and appearance-based energy. An internal energy term based on the centerline positions and radii is used as the smooth constraint. We further improve this approach by incorporating a released constraint on object intensity distribution and the directional distances such that the true boundary could be the optimal solution to the energy optimization even though the object may not have the highest intensity values in the image.

Denote $\mathbf{o}$ as a unit vector pointing from the centerline position to the boundary point, the offset-medialness $M_o(\mathbf{x}, r)$ of a cross section is calculated using the gradient of the intensity along $\mathbf{o}$:

$$M_o(\mathbf{x}, r) = \frac{1}{m} \sum_{j=1}^m -\mathbf{o}_j \cdot \nabla I(\mathbf{x} + r\mathbf{o}_j) \quad (6)$$

where m is the number of selected points on the boundary, r is the radius of the circle, $\mathbf{x}$ is the position of the center point and $\mathbf{o}_j$ is the unit vector from the center point to the j -th boundary point. The proposed new appearance-based energy term is defined as the difference between the current circle and the boundary of the region of interest (ROI). First, the intensity distribution of the vessel is estimated using (4) with R_M denoting the current detected region inside the vessel. Then based on the estimated p.d.f, each voxel is assigned a probability value and a mean thresholding is applied to generate a binary image. After that, a region growing is applied from the initial centerline and the result is treated as the ROI, followed by a canny edge detection to extract the boundary. Finally, the difference d between the points on the circle ($\mathbf{x} + r\mathbf{o}_j$) and the corresponding points ($\tilde{\mathbf{x}}_j$) on the ROI is calculated along directions $\mathbf{o}_j$, $j = 0, 1, 2, \dots$ (Figure 3). The proposed appearance-based energy term $M_c(\mathbf{x}, r)$ for each cross section is defined as the average unsigned directional distance:

$$M_c(\mathbf{x}, r) = \frac{1}{m} \sum_{j=0}^m d(\mathbf{x} + r\mathbf{o}_j, \tilde{\mathbf{x}}_j) \quad (7)$$

Figure 3 shows the advantages of using the proposed directional distance for energy calculation. Figure 3(a) shows a case when the current estimated center point is very close to the actual center point. In this case, the conventional shortest distance in level set scheme works fine and our proposed appearance-based energy calculation is very similar to it. Figure 3(b) shows a case when the estimated center point is very close to the boundary point. In this case, the shortest distance in level set scheme will lead the contour shrink to the boundary point P_1 , instead of pulling to the ROI boundary toward P_2 . While the

proposed directional distance works well in this case as it tries to reduce the distance d_2 , thus pulling the contour toward P_2 .

The overall external energy E_{ext} for one cross section at center point $\mathbf{x}_i$ is defined as the weighted sum of the offset-medialness and the appearance-based energy terms. In addition, the internal energy for each cross section is defined as:

$$E_{int}(i) = \frac{\beta}{4} (\|\mathbf{x}_i - \mathbf{x}_{i-1}\|^2 + \|\mathbf{x}_i - \mathbf{x}_{i+1}\|^2) + \frac{1-\beta}{4} ((r_i - r_{i-1})^2 + (r_i - r_{i+1})^2) \quad (8)$$

where $\beta = 0.5$ is a constant parameter to balance the contribution of each term. Thus, the total energy for the snake model is defined as:

$$\hat{E}_{snake} = \sum_{i=1}^N [\lambda E_{ext}(i) + (1 - \lambda) E_{int}(i)] \quad (9)$$

where N is the total number of center points in the initial centerline, and $\lambda = 0.8$ is a constant parameter to balance the contribution of each energy term in the overall energy calculation. The evolution of the snake model is based on the iterative gradient descent method, which minimizes $\hat{E}_{snake}$ with respect to both the center point location $\mathbf{x}_i$ and the radii r_i . Compared to the energy definition in [18], our design on appearance-based energy term releases the constraint of object intensity distribution, which makes it possible to detect objects whose intensity values are similar or lower than their surrounding backgrounds. Furthermore, by applying directional distance in the snake model, the algorithm is more robust against the location of the initial center point.

III. Experimental results

To evaluate the performance, the proposed method is applied to clinical coronary CTA images as well as synthetic CTA images. We adopt the evaluation measurements defined in [19]. Three overlap measurements, overlap (OV), overlap until the first error (OF), and overlap with the clinically relevant part of the vessel (OT), are used to assess the ability of centerline tracking. One distance measurement, average distance inside the vessel (AI), is used to assess the accuracy of centerline tracking. Figure 4 illustrates the definition of different terms used in these measures. The overlap measurements are defined as:

$$\begin{aligned} OV &= \frac{(TP \cap EST) + (TP \cap REF)}{EST + REF} \\ OF &= \frac{TP \cap RT \cap REF}{REF} \\ OT &= \frac{(TP \cap RF \cap REF) + (TP \cap RF \cap EST)}{(RF \cap REF) + (RF \cap EST)} \end{aligned} \quad (10)$$

The distance measurement AI is the average distance between the detected path and the reference of the TP region. The real clinical coronary CTA images are acquired with a typical resolution of $0.36\text{mm} \times 0.36\text{mm} \times 0.40\text{mm}$. Four major coronary arteries are extracted from a coronary CTA image, namely, Right Coronary Artery (RCA), Left Anterior Descending branch (LAD), Left Circumflex artery (LCX), and one large side branch of the main coronary arteries. The reference standards for the centerlines are provided by the average of three trained observers. The proposed method is applied to 8 CTA datasets and a total of 32 coronary arteries are tracked and measured. Figure 5 shows the extracted centerlines and corresponding segmentation results. Table 1 summarizes the comparison results of the proposed method with other semi-automated centerline extraction methods

designed for coronary artery extraction, including Multi-Hypothesis Tracking (MHT)[20], Tracer [21], Two Point Minimum Cost (TPMC) [22], Knowledge Based Minimum Path (KBMP) [23], and Coronary Tree Morphology Reconstruction (CTMR)[24]. Our method is the fastest, archives good tracking ability (94.7% overlap) within an average distance inside the vessel of 0.36mm. Besides, our proposed method is able to estimate the radii information of the coronary arteries. In the table, the “points per vessel” indicates how many points should be manually provided on average for each artery to be extracted. The OF value of our method is intermediate among all results. This indicates that error occurs at earlier stage of the tracking because of the thinness of the vessels. However the good OV value also indicates the tracking can be well adjusted to come back to the right traces.

Synthetic coronary CTA images are generated to simulate blood vessels with pre-defined centerlines and circular cross sections. Figure 6 shows an example result for the centerline extraction and vessel segmentation in a synthetic CTA image. On average the error for radii estimation is less than 0.1mm and the average AI is 0.08mm.

IV. Conclusion

We present a highly automated method to segment arteries in CTA images. The method consists of a novel centerline tracking method and an improved generalize cylinder model for centerline refinement and tubular structure segmentation. In the tracking procedure, both the first and second order geometric moments based directions are adopted to improve accuracy and ensure that the tracking is always inside the tubular structures. The tracking result is further refined using an improved generalized cylinder structure based parametric snake model. The evaluation shows that the proposed method has very good tracking ability with a sub-voxel tracking accuracy for coronary CTA images.

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Fig. 1. Centerline tracking example. (a) direction $\mathbf{u}$; (b) direction $\mathbf{v}$; (c) estimated local line direction $\mathbf{w}$.

Fig. 2.
Flowchart of the proposed artery tracking procedure.

Fig. 3.
Advantages of using directional distance in energy calculation.

Fig. 4.

An illustration of the different terms used in the measurements. REF, EST indicates the reference and estimated centerline respectively; TP (True Positive) are the regions where the estimated path is inside the vessel, FN (False Negative) are the rest regions. RF, RT are the region before the first error and the region with a radius larger than 1.5mm respectively.

Fig. 5. Results on coronary artery segmentation. Left column: centerline extraction results with red lines representing reference standards and black lines the detected results. Right column: surface rendering of artery segmentation results.

Fig. 6. Vessel segmentation and radius estimation results for a sample synthetic coronary CTA image. (a) vessel segmentation results with yellow region representing the vessel boundary, red and black lines indicating the ground truth and detected centerline respectively. (b) radii estimation results compared with references.

Table 1

Average measurement of different methods

Method	OV (%)	OF (%)	OT (%)	AI (mm)	Time (min)	Points per vessel
MHT	99.3	94.6	99.5	0.24	6	2.6
Tracer	92.2	68.0	92.8	0.28	30	2
TPMC	93.3	67.8	93.5	0.48	12	2
KBMP	98.1	92.7	98.1	0.41	420	1
CTMR	72.6	45.6	73.8	0.67	30	1
<i>Ours</i>	94.7	69.6	95.2	0.36	3	2