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Adaptive particle filtering for coronary artery segmentation from 3D CT angiograms

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ABSTRACT

Considering vessel segmentation as an iterative tracking process, we propose a new Bayesian tracking algorithm based on particle filters for the delineation of coronary arteries from 3D computed tomography angiograms. It relies on a medial-based geometric model, learned by kernel density estimation, and on a simple, fast and discriminative flux-based image feature. Combining a new sampling scheme and a mean-shift clustering for bifurcation detection and result extraction leads to an efficient and robust method. Results on a database of 61 volumes demonstrate the effectiveness of the proposed approach, with an overall Dice coefficient of 86.2% (and 92.5% on clinically relevant vessels), and a good accuracy of centerline position and radius estimation (errors below the image resolution).

1. Introduction

In biomedical applications, vascular structures are often of critical importance for diagnosis, treatment and surgery planning. Vessels are thin, elongated and complex structures embedded in increasingly large images. Manual delineation, although still heavily used in clinical routines, has become a considerable burden and automatic or semi-automatic segmentation remains challenging.

Vascular segmentation has received considerable attention in the literature [41]. A popular approach is to consider the segmentation as an iterative, *tracking* process. Classical region-growing techniques can be seen as primitive representatives of this class of methods. Front propagation techniques allow for a refined analysis by imposing a structurally coherent exploration process. The robustness of local deterministic tracking is generally limited by the necessity of using low-level causal criteria. In some settings, the tracking problem has been formulated as the extraction of globally optimal paths [11,43,46]. Another approach, which is increasingly popular, is the use of stochastic Bayesian tracking algorithms such as particle filters [1,16,17,42,49,52,54,55,62–64,68]. Such algorithms have demonstrated particular robustness while allowing for high-level modeling.

In this paper, we propose a new Bayesian, stochastic tracking algorithm for the delineation of coronary arteries from 3D Computed Tomography Angiograms (CTA). Our approach is inspired by recent developments in particle filtering designs [1,16,17,42,52,54]. It relies on a medial-based geometric model and on a simple, fast and discriminative flux-based image feature [44], described in Section 3. The proposed method includes the following contributions:

- the design of a geometric vascular model described in Section 2;
- the introduction of a non-parametric Bayesian model, learned by kernel density estimation [56] from a ground-truth database of manually segmented datasets (Section 4);
- the design of a new sampling scheme, *Adaptive Auxiliary Particle Filtering* (AAPF), described in Sections 6 and 7 after briefly recalling the bases of particle filters in Section 5;
- the use of mean-shift clustering [9,21] for bifurcation detection and coronary tree extraction, along with the proposal of algorithmic refinements for increased computational efficiency (Section 7).

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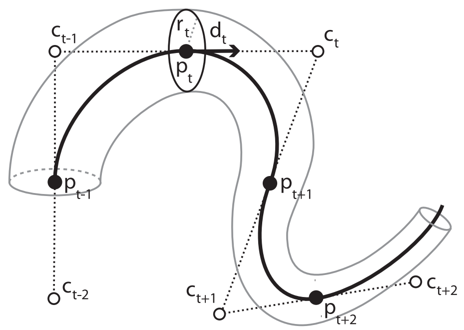

Fig. 1. Discrete medial-based geometric model (see text for notations).

A series of experiments is presented in Section 8, illustrating theoretical and practical properties of our approach, along with qualitative and quantitative evaluation on clinical data.

2. Geometric model

In this work, we chose to model vascular structures using a medial representation inspired by general shape models such as the Medial Axis Transform (MAT) from [4,5] and the Smoothed Local Symmetry (SLS) model from [6]. The main idea behind medial models applied to 3D elongated structures such as vessels is to represent the shapes of interest through their main axis, the *centerline* curve lying at the center of the vessel (Fig. 1).

We combine centerline- and cross-section-based information to constrain and reduce the parameter space with a particular discrete parameterization, illustrated in Fig. 1. Cross-sections, defined in locally orthogonal planes along the curved centerline, are assumed to be circular. This hypothesis is reasonable for the description of small scale vessels such as coronary arteries and enables straightforward parameterization. The centerline curve is discretized as a series of centerline points $\{p_t\}_{t=0,\ldots,L}$, with associated radius values and tangential direction vectors, noted $\{r_t\}$ and $\{d_t\}$, respectively. Radius values and tangent directions define cross-sectional contours. A vascular segment is modeled as a series of triplets $x_{0:L} = \{(p_t, r_t, d_t)\}_{t=0,\ldots,L}$. Individual elements $x_t = (p_t, r_t, d_t)$ are used as the *state* variables of the vessel model being optimized during the tracking process. We assume an order on the states, denoted by subscripts $t \in [\![0, L]\!]$. For coronary arteries, a natural ordering is from the ostium x_0 (origin of the artery branching off the aorta) to their distal ends x_L. Tangential directions $\{d_t\}$ are defined thanks to *control* points $\{c_t\}$: $d_t = \frac{c_t - c_{t-1}}{\|c_t - c_{t-1}\|}$.

To further constrain our geometric model, we propose to link the positions of centerline and control points, indirectly coupling centerline points and tangent directions, as:

$$p_t = \frac{c_t + c_{t-1}}{2} \tag{1}$$

This scheme, closely related to cardinal spline models, can be viewed as an artificial parameterization simplifying the formulation of our model and reducing its dimensionality. It makes possible a stable definition of tangential directions even in areas of high curvature. By doing so, control points constrain both the definition of tangential directions and the discretization of the centerline curve. States $x_t = (p_t, r_t, d_t)$ of our model can be described alternatively as $x_t = (c_{t-1}, c_t, r_t)$ given control points and radiuses, both being equivalent. The overall dimensionality of our model is thus limited to 4D (3D control point locations + radius values).

By convention, we consider that the first centerline point p_0 is fixed and that the first tangential direction d_0 is defined solely by c_0. It is equivalent to considering an implicit control point $c_{-1} = 2p_0 - c_0$. Whenever needed, centerline points and corresponding tangents can be used to conveniently interpolate the centerline curve, *e.g.* using cubic Hermite splines.

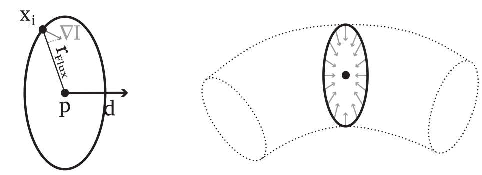

Fig. 2. `Flux` image feature. Discretized cross-sectional pattern defined by parameters (p, r_{flux}, d), with $r_{\texttt{Flux}}$ the *test* radius. For each x_i, the gradient vector $\nabla I(x_i)$ is projected on the inward radial direction, $u(x_i) = \frac{p - x_i}{\|p - x_i\|}$.

One key parameter of our model is the spacing between successive control points $s = \|c_{t-1} - c_t\|$. This discretization step directly impacts the expressive power of the model. As it gets smaller, the model is able to depict accurately highly curved vessels. In this work, we used a fixed discretization step of the order of the data intra-slice resolution (0.3mm) to provide an accurate description of typical coronary arteries.

3. Flux-based vessel-dedicated feature

To feed our geometric model with image information, we employ a fast, discriminative image feature, referred to as `MFlux` [44]. This feature exploits *gradient flux* for the detection of elongated structures with circular cross-sections.

As demonstrated in [12,31,35,60], flux-based segmentation methods are well adapted for the extraction of thin, low-contrast vessels. They exploit the orientation of the gradient vectors by computing the gradient flux through the surface of the extracted object. For CTA images, we assume that vessels are hyper-intense, and maximize the *inward* flux through the circular *cross-sections* of the model. For slowly narrowing or widening vessels, the radial directions give a reasonable approximation of the local normals to the surface (see Fig. 2). After equi-angular discretization of the cross-section (orthogonal to d) perimeter with radius r into N points x_i, we obtain the following cross-sectional flux measure:

$$\texttt{Flux}(p, r, d) = \frac{1}{N}\sum_{i=1}^{N}\langle \nabla I(x_i), u_i\rangle \tag{2}$$

with $\nabla I(x_i)$ the gradient vector at point x_i and $u_i = \frac{p - x_i}{|p - x_i|}$ the inward radial direction as defined in Fig. 2. Being a linear feature, $Flux(p, r, d)$ is prone to false positive high-values at step-edges, as already mentioned by [38]. In our case, this behavior is particularly problematic along the heart chambers. A non-linear combination was therefore proposed to pair diametrically opposed points (x_i, x_i^{π}) and retain the *minimal* flux contribution per pair, similarly to what was done in 2D by [38]. The `MFlux` feature is defined as:

$$\texttt{MFlux}(p, r, d) = \frac{2}{N}\sum_{i=1}^{\frac{N}{2}}\min(\langle \nabla I(x_i), u_i\rangle, \langle \nabla I(x_i^{\pi}), u_i^{\pi}\rangle)$$

with $x_i^{\pi} = x_{\frac{N}{2}+i}$ for an even number N of cross-sectional points.

The implementation of `MFlux` is particularly straightforward and computationally efficient. In the present work, we used $N = 8$ cross-sectional points and employed tri-linear interpolation for the computation of image gradient vectors.

`MFlux` responses are used as *image features* and combined with model-based prior knowledge, within the Bayesian tracking model described in the next section.

4. Bayesian vessel model

Our geometric model defines a vessel as a discrete ordered chain of states $x_{0:L} = \{(p_t, r_t, d_t)\}_{t=0,\ldots,L}$ with p_t the centerline points, r_t the radius values and d_t the local tangential directions. A particular chain