Deep Recursive Bayesian Maximal Path for Fully Automatic Extraction of Coronary Arteries in CT Images

Byunghwan Jeon[1], Sunghee Jung[1,2], Hackjoon Shim[1] and Hyuk-Jae Chang[1]

[1]CONNECT-AI Research Center, College of Medicine, Yonsei University
[2]Brain Korea 21 PLUS Project for Medical Science, Yonsei University

Abstract

Extraction of coronary arteries in coronary computed tomography angiography (CCTA) is a prerequisite for quantification of coronary lesions. Coronary artery is a curvilinear structure that has multiple branches. In this paper, we propose an automatic tracking method to identify the trajectories from the coronary ostium to each distal end. A tangent patch-based convolutional neural network (CNN) is utilized for measuring robust vesselness, which roles a likelihood function in our stochastic tracking algorithm. Tangent patches can represent cross-sections of coronary arteries that have circular shapes. Thus, 2D tangent patches are assumed to include enough features of curvilinear objects in 3D and using 2D patches significantly reduces computational complexity. The posterior density on the spherical surface is represented by random particles, and the associated weights are then determined using a tangent patch-based CNN. Since coronary vasculature has multiple bifurcations, the majority and minority (M&m) system is employed to determine the direction of the main or branching path adaptively. The proposed method is compared with three commercial workstations and two conventional methods from the academic literature.

1 Introduction

Extraction of coronary arteries in coronary computed tomography angiography (CCTA) is a prerequisite for quantification of coronary lesions. Coronary arteries are represented as tree structures in 3-dimensional (D) volume image and elongated with inhomogeneous contrast enhancement on the lesion. Due to its sparsity, automatic or semi-automatic segmentation remains challenging. In the literature [1, 2], there has been considerable attention to the analysis of curvilinear or vascular structures. The most relevant approaches for coronary artery extraction are based on tracking along the vessel segment by varying measurement models and using prior knowledge. In such a stochastic framework, the most important part is an accurate vesselness measure, which can affect tracking results. In other words, the critical point of the tracking method is building a robust sensor in order to determine the vessel signal correctly.

2 Hybrid Tracking Scheme using Convolutional Neural Network

A coronary artery found in 3-D CCTA is a thin, elongated and tree-structured object. Our system aims at recovering a vascular tree as a chain of spheres centers $X_T = x_0, ..., x_T$ which are estimated given the observation, the stationary image $Y_t = Y, \forall t$. The recursive fashion of Maximum a Posteriori (MAP) estimation is a feasible solver for the most probable path of the coronary artery [3]. Then,

33rd Conference on Neural Information Processing Systems (NeurIPS 2019), Vancouver, Canada.

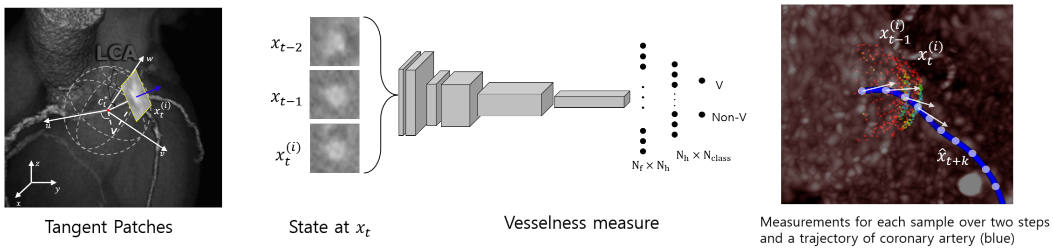

Figure 1: Geometry of a tangent plane on a sphere for patch generation (left), input patches consist of a current candidate patch and two preceding patches based on second-order Markovian property (mid), the samples on spheres with two steps and their measured weights are also visualized with a color scale (blue-red) for vessel and non-vessel (right).

a Monte-Carlo approximation of the posterior distribution $p(X_t|Y)$ by the weighted population of N_t discrete samples $S_t = \{x_t^{(i)}, w_t^{(i)}\}_{i=1}^{N_T}$. A weight $w_t^{(i)}$ is evaluated from the posterior distribution in Eq (1). The state vector $x_t = \{c_t, n_t, \Phi_t\}$ at time t contains the centerline point $c_t \in \mathbb{R}^3$, the orientation n_t and the tangent patch Φ_t whose centroid and normal is c_t and n_t, respectively. $\{x_t^{(i,j)}\}$ is potential successors of $x_{t-1}^{(i)}$.

$$w_t^{(i,j)} \propto w_{t-1}^{(i)} p(Y|x_t^{(i,j)}) p(x_t^{(i,j)}|x_{t-1}^{(i)}) \tag{1}$$

where $p(Y|x_t^{(i,j)})$ and $p(x_t^{(i,j)}|x_{t-1}^{(i)})$ are the likelihood and the prior, respectively.

$$p(Y|x_t^{(i,j)}) = p(Y|\Phi_t^{(i,j)}) \approx \frac{e^{y_V}}{e^{y_V} + e^{y_{NV}}} \tag{2}$$

where y_V and y_{NV} represent classes in a vessel and non-vessel respectively, and Φ_t is simply a small image mapped with Hounsfield unit (HU, -1000 $\leq$ Y $\leq$ 3000) that is applied by Z-normalization for CNN training. The softmax output from our CNN module in Eq. (2) is denoted to vesselness probability. In our model, the likelihood highly depends on the performance of the CNN based vessel sensor. The tracking process is described in Fig. 1. $p(Y|x_t^{(i,j)})$ is approximated by the trained model, and $p(x_t^{(i,j)}|x_{t-1}^{(i)})$ is computed by the distribution similarity between the tangent patches at time $t-1$ and t using Kullback-Leibler divergence.

$$\hat{c}_t = \hat{c}_{t-1} + \gamma \hat{n}_{t-1}, \hat{n}_{t-1} = \sum_{i=1}^{N_T} w_t^{(i)} c_t^{(i)} - \hat{c}_{t-1}, \tag{3}$$

where the normal $\hat{n}_{t-1}$ approximates a direction of blood flow at step $t-1$, and γ is a fixed step size. The centerline point $\hat{c}_{t-1}$ in Eq. 3 is updated toward the direction of the estimated next location $\sum_{i=1}^{N_T} w_t^{(i)} c_t^{(i)}$ in the vessel trajectory. For the branching point, the population for each step is clustered into two point sets, majority (M) and minority (m). The mean point of class m is used for the new branching seed of tracker. An example of an automatic result is presented in Fig. 2.

3 Experiment

The method is automatically initialized with a seed point, which is the coronary ostium, and a direction by the method [4]. The state vector x_0 contains c_0, n_0, Φ_0, and Φ_0 is simply drawn based on c_0 and n_0.

3.1 Evaluation on CTA database

The robustness and accuracy are evaluated with the criteria proposed in [5]. Experiments were performed using an NVIDIA Titan Xp GPU. We trained our CNN model with a total 170,000 tangent

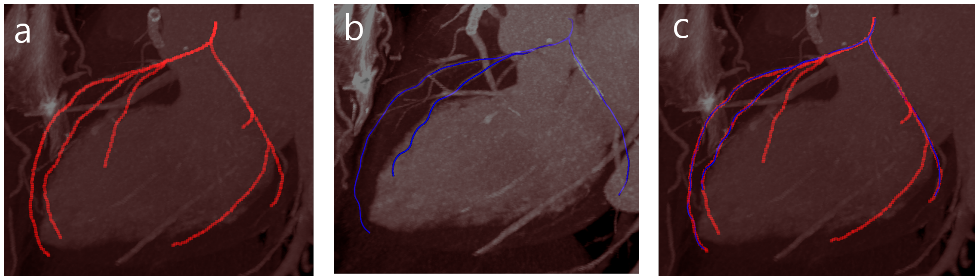

Figure 2: (a) the initial results of tree extraction have not only the main coronary arteries but also some small branches, (b) ground truth of three main coronary arteries from the same case in a, (c) ground truth and the result by the proposed method is visualized.

		Solver					
		QAngioCT[6]	Xelis[7]	Vitrea[8]	AS[9]	AAPF[10]	Proposed
Measure	OV	0.86	0.78	0.86	0.84	0.86	0.92
	OT	0.88	0.80	0.89	0.88	0.92	0.93
	AI	0.36	-	-	-	0.25	0.36

Table 1: Comparison with other methods including commercial workstations. All the methods are compared with the same public dataset, eight patients, 32 vessels except AAPF method. AAPF used a 51 private CT images.

patches Φ_t extracted from centerline GT [5] to measure the vesselness. CNN model is trained based on Leave-One-Out rule.

- OV: Total overlap, $\frac{||TPM||+||TPR||}{||TPM||+||TPR||+||FN||+||FP||}$.
- OT: OV of the extracted centerline with the clinically relevant part of the vessel $(radius \leq 0.75mm)$
- AI: The average inside accuracy metric (AI) measures the average distance between the reference, $A(x) = \sqrt{1/n\Sigma(d(p(x), p_i))^2}$, and extracted centerline for automatically extracted points that are within the radius of the reference centerline.

4 Evaluation and results

In this paper, we proposed a CNN based stochastic tracking method for the extraction of coronary arteries from CCTA. Three workstations [8, 7, 6] and two methods from the published papers [9, 10] were compared with the proposed method in Table. 1 on eight cases with 32 single vessels provided in CAT08 [5]. In terms of overlap, the proposed method obtained an average OV of 92%, an average OT of 93%. In terms of accuracy, the proposed method obtained AI of 0.36mm, which is similar to the typical width of a voxel and smaller than the spacing between slices in the dataset. In the comparison in Fig. 1, the proposed method showed higher performance in OV and OT, which measure how far the coronary artery has been tracked. The proposed method can be improved by centerline refinement through post-processing. The proposed method shows a higher performance of coronary artery extraction as an approach combining CNN with a probabilistic framework.

5 Conclusion

In this paper, we proposed a deep learning-based tracking method for the extraction of coronary arteries from CT images. The experiment shows comparable results with the state-of-the-art method. However, this hybrid approach still has the potential to be improved. We are currently improving a CNN model and planning to test the method with much more CT images to validate the robustness.

6 Acknowledgement

This research was supported by the Leading Foreign Research Institute Recruitment Program through the National Research Foundation of Korea funded by the Ministry of Science, ICT Future Planning (No. 2012027176).

References

[1] David Lesage, Elsa D Angelini, Isabelle Bloch, and Gareth Funka-Lea. A review of 3d vessel lumen segmentation techniques: Models, features and extraction schemes. *Medical image analysis*, 13(6):819–845, 2009.

[2] Pedro Bibiloni, M González-Hidalgo, and Sebastià Massanet. A survey on curvilinear object segmentation in multiple applications. *Pattern Recognition*, 60:949–970, 2016.

[3] Arnaud Doucet, Nando De Freitas, and Neil Gordon. An introduction to sequential monte carlo methods. In *Sequential Monte Carlo methods in practice*, pages 3–14. Springer, 2001.

[4] Byunghwan Jeon, Yoonmi Hong, Dongjin Han, Yeonggul Jang, Sunghee Jung, Youngtaek Hong, Seongmin Ha, Hackjoon Shim, and Hyuk-Jae Chang. Maximum a posteriori estimation method for aorta localization and coronary seed identification. *Pattern Recognition*, 68:222–232, 2017.

[5] Michiel Schaap, Coert T Metz, Theo van Walsum, Alina G van der Giessen, Annick C Weustink, Nico R Mollet, Christian Bauer, Hrvoje Bogunović, Carlos Castro, Xiang Deng, et al. Standardized evaluation methodology and reference database for evaluating coronary artery centerline extraction algorithms. *Medical image analysis*, 13(5):701–714, 2009.

[6] Medis. `https://www.medis.nl/`.

[7] Infinitt. `https://www.infinitt.com/`.

[8] Vital. `https://www.vitalimages.com/`.

[9] Dongjin Han, Hackjoon Shim, Byunghwan Jeon, Yeonggul Jang, Youngtaek Hong, Sunghee Jung, Seongmin Ha, and Hyuk-Jae Chang. Automatic coronary artery segmentation using active search for branches and seemingly disconnected vessel segments from coronary ct angiography. *PloS one*, 11(8):e0156837, 2016.

[10] David Lesage, Elsa D Angelini, Gareth Funka-Lea, and Isabelle Bloch. Adaptive particle filtering for coronary artery segmentation from 3d ct angiograms. *Computer Vision and Image Understanding*, 151:29–46, 2016.