

A Multi-resolution Multi-model Method for Coronary Centerline Extraction Based on Minimal Path

Dengqiang Jia¹, Wenzhe Shi², Daniel Rueckert², Liu Liu¹,
Sebastien Ourselin³, and Xiahai Zhuang¹(✉)

¹ School of Naval Architecture, Ocean and Civil Engineering,
Shanghai Jiao Tong University, Shanghai, China
zhuangxiahai@163.com

² Biomedical Image Analysis Group, Imperial College London, London, UK

³ Centre for Medical Image Computing, University College London, London,
UK

Abstract. Extracting centerlines of coronary arteries is challenging but important in clinical applications of cardiac computed tomography angiography (CTA). Since manual annotation of coronary arteries is time-consuming, labor-intensive and subject to intra- and inter-variations, we propose a new method to fully automatically extract the coronary centerlines. We first develop a new image filter which generates pixels with salient vessel features within a given window. This filter hence can capture sparsely distributed but important vessel points, enabling the minimal path (MP) process to track the key centerline points at different resolution of the images. Then, we reformulate the filter for multi-resolution fast marching, which not only can speed up the coronary tracking process, but also can help the front propagation to step over the indistinct segments of the coronary artery such as at the locations of stenosis. We embed this scheme into the MP framework to develop a multi-resolution multi-model approach (MMP), where the extracted centerlines from low-resolution MP serve as prior and constraints for the high-resolution process. We evaluated the performance of this method using the Rotterdam CTA training data and the coronary artery algorithm evaluation framework. The average inside of our extraction was 0.51 mm and the overlap was 72.9 %. The mean runtime on the original resolution CTA images was 3.4 min using the MMP method.

1 Introduction

Extracting coronary centerlines from cardiac Computed Tomography Angiography (CTA) is important in clinics, which facilitates the diagnosis and quantification of coronary stenosis. A number of works have focused on extracting the complete coronary artery tree [1]. However, it is difficult to automatically extract the main branches of the coronary tree. The minimal path (MP) framework has been extended for this purpose, either to extract a single branch [2–4] or multiple branches based on initialized seed points [5]. However, the extraction could perform poorly at the indistinct segments, such as due to the occlusion, calcifications, imaging artifacts, or insufficient contrast agent.

The detection methods also tend to be challenged, when the seed points are off the coronary or the branch has discontinues segments due to bypass surgeries or image artifacts. Zheng et al. [6, 7] adopted a model-driven approach to automatically extract and recognize the main branches through a learning-based algorithm, which employed 108 CTA volumes, with manual annotations of the coronary centerlines, to train their learning algorithm. Liu et al. proposed a model-guided directional MP method for automatic extraction of coronary centerlines [8, 9]. The model used in this method helps tracking the coronary branch of interest correctly. However, the fast marching method (FMM) iteration is still computationally expensive and the front propagation can be blocked due to the indistinct segments of the coronary artery.

In this work, we develop a new method based on the multi-resolution and multi-model MP framework. First, we propose a new image filter which identifies points with salient vessel features within a given window. This filter can be used to generate feature maps at different resolutions, enabling the MP process to track the centerline key points at different resolutions of the images. This multi-resolution approach has two advantages:

- (1) Finding one salient point within a big window, instead of all vessel points, can help stepping over the invisible sites of the coronary at some locations such as the severe stenosis, thus improve the performance of the MP method.
- (2) It can speed up the FMM process and consequently the back tracking at a coarse resolution to provide a more efficient centerline extraction method.

Second, we develop a multi-model method, based on the multi-resolution MP framework, referred to as MMP, to extract multiple branches of the coronary arteries. The MMP method is capable of efficiently tracking the desired branches with great length.

The rest of the paper is organized as follows: Sect. 2 describes the proposed new filter. Section 3 introduces the MMP framework. We provide the experiments and results in Sect. 4 and finally conclude this work in Sect. 5.

2 A Filter Preserving Salient Vessel Features

In MP-based centerline extraction, one major issue is the indistinct segments in the vessel, which easily resulting a deviation of the FMM and consequently tracking into wrong path; and the other is the computation complexity of FMM iteration, which is $O(N\log N)$, where N denotes the number of pixel points [10, 18]. In this section, we introduce a new image filter which can provide CTA images with arbitrary low resolution while enhancing the vesselness of coronary arteries for MP process.

The original vesselness filter proposed by Frangi et al. enhances the tube structure of an image by computing the Hessian matrix and its eigenvalues [12]:

$$v(x) \triangleq \begin{cases} 0 & \text{if } \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ (1 - e^{-\frac{\kappa_A^2}{2\sigma^2}})e^{-\frac{\kappa_B^2}{2\beta^2}}(1 - e^{-\frac{\kappa_C^2}{2\sigma^2}}) & \text{otherwise} \end{cases} \quad (1)$$

where v is the vesseness at pixel x , λ_k denotes the ordered eigenvalues, $\mathcal{R}_A \triangleq \left| \frac{\lambda_2}{\lambda_3} \right|$, $\mathcal{R}_B \triangleq \frac{|\lambda_1|}{\sqrt{|\lambda_2 \lambda_3|}}$, $S \triangleq \sqrt{\sum_j \lambda_j^2}$; α , β , and c tune the sensitivity of the filters.

To achieve the multi-resolution FMM, one needs to obtain the image intensity f and vesseness v with salient vessel features at different resolution. Since MP tracks the vessel centerlines based on the minimal cost of the potential function, we propose to compute the image intensity and vesseness within a given window as follows,

$$f_W(x) = f(\operatorname{argmin}_{x \in W_x} P(x)) \text{ and } v_W(x) = v(\operatorname{argmin}_{x \in W_x} P(x)), \quad (2)$$

where W_x denotes the volume defined by the given window, $P(x)$ is the potential function proposed in [13],

$$P(x) = \frac{1}{v(x)^\alpha * s(x)^\beta + \epsilon} \quad (3)$$

Here, $s(x)$ is the intensity similarity term.

The proposed filter can down sample the intensity and vesseness images of a CTA volume into any resolutions, which is determined by the size of the given window W . The advantage of the proposed filter for down sampling the CTA images is that it can select the points with the most salient vessel features within the window to save the vessel information at the low-resolution images for MP tracking. This is unlike the

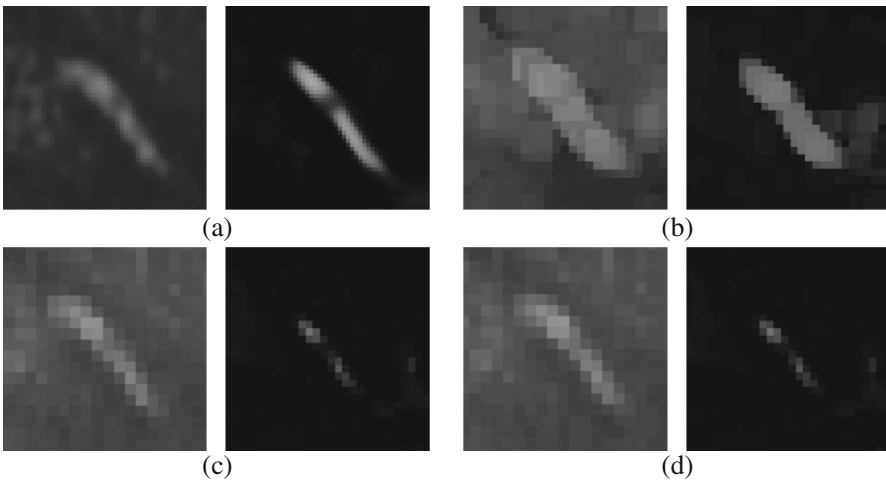


Fig. 1. Illustration of the vessel images: (a) the original resolution CTA image (left) and corresponding vesseness image (right); (b) the down-sampled images using the proposed filter; (c) the down-sampled images using the nearest interpolation; (d) the down-sampled images using the B-Spline interpolation.

conventional down-sampling methods which blur the original images and thus lose the important vessel characteristics after down-sampling. Figure 1 provides the examples of an original CTA and vesselness image pair and the down-sampled images by the proposed filter and the nearest and B-Spline interpolation methods. The occlusive vessel is then *connected* and enhanced by the proposed filter at low resolution images. By contrast, the other two methods blue weaken the vessel features in the resulting images.

3 Multi-resolution Multi-model Minimal Path for Centerline Extraction

3.1 The Minimal Path at Multi-resolution Images

In the MP framework [14], a decreasing potential function $P(x)$ is given to build an energy functional $E: \mathcal{C}_{a_1, a_2} \rightarrow \mathbb{R}^+$,

$$E(C) = \int_C \{P(C(s)) + w\} ds = \int_C \{\tilde{P}(C(s))\} ds, \quad (4)$$

where \mathcal{C}_{a_1, a_2} is the set of all paths joining a_1 to a_2 , s is the arc-length parameter, w is a positive regularization factor. MP computes the minimal action map $U: \Omega \rightarrow \mathbb{R}^+$ associated to a_1 is used to solve the minimization problem. Conventional, U is updated on the neighbor pixels of the current propagation. In this work, we propose to update this map solely on one pixel within a given window W_x which controls the resolution of the action map, i.e. $U': \Omega/|W| \rightarrow \mathbb{R}^+$. Since $\{W_x\}$ can be user-defined, the FMM and MP hence can *operate on a different resolution of the action map*, given the sizes of windows are set differently at different regions or iteration steps.

Furthermore, the potential function P is generally defined related to the intensity and vesselness such as in (3). In the model-guided MP, we further include the direction of the coronary model as follow,

$$P(x) = \frac{1}{v(x)^\alpha \cdot s(x)^\beta \cdot d(x) + \varepsilon} \quad (5)$$

where $d(x)$ is the direction information derived from the model [9].

3.2 Multi-resolution and Multi-model Minimal Path

To improve the performance of MP for coronary artery extraction, we propose to use multiple models for the model-guided MP, resembling the widely used multi-atlas segmentation strategy [16, 17], which operates on multi-resolution images using the proposed salient vesselness filter, i.e. MMP, which works as follows:

- (1) MMP first performs the multi-model MP using the low-resolution intensity (LRI) images and low-resolution vesselness (LRV) images. This can efficiently generate a set of centerlines, each of which comes from one model-guided MP.
- (2) Then an optimal centerline is identified based on the length of the centerline and closeness to the branch of interests. Based on the selected result, we identify the optimal model and generate a mask, as prior and a constraint for the next tracking using higher resolution images.
- (3) The previous tracking-and-selecting step iterates until the original resolution intensity (ORI) and vesselness (ORV) images are reached. The final coronary centerline is generated from the original images. Figure 2 provides the illustration of the MMP method.

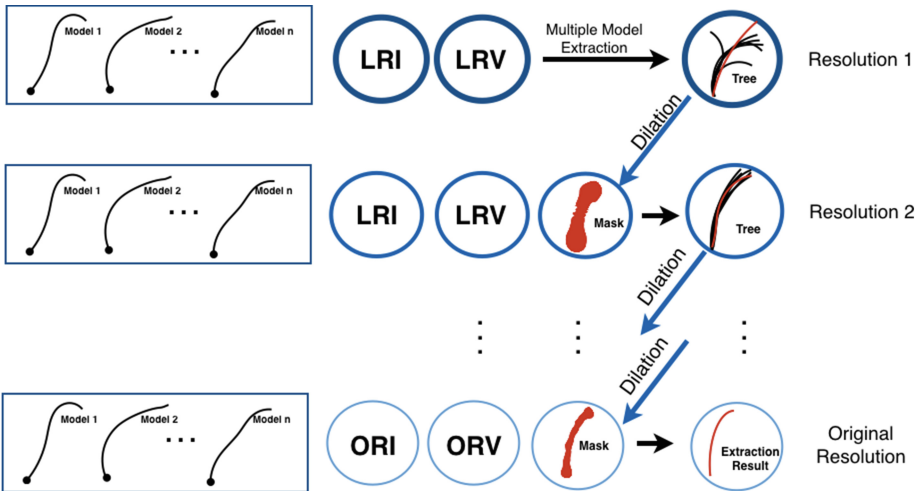


Fig. 2. Diagram illustrating the MMP method extracting the centerline of a main branch of the coronary artery tree.

3.3 Initialization of Coronary Model and Ostium Detection

The coronary model, a coronary centerline extracted from a training CTA, contains the shape of the artery and the line direction at any location. By mapping this coronary model to the target CTA using a hierarchical registration scheme [11], one can extract the direction information from the model for local direction-guided FMM [9]. We employ the learning-based ostium detection based on Haar-like features and the probability boosting tree framework [7, 8], and transform the coronary model to the target CTA by aligning the ostium of the coronary model to corresponding one in the target image. This ostium mapping is first initialized with a deformable registration between the segmented target image and the model CTA [11].

4 Results

To analyze the performance of the proposed method, we used the eight datasets with gold standard from the Rotterdam database [15]. Each of them has manually annotated right coronary artery (RCA), left anterior descending artery (LAD), left circumflex artery (LCX), and a randomly picked large side branch. Methods were evaluated with the overlap measurement and accuracy inside (AI) metrics [15]. The overlap metric includes overlap (OV), overlap until first error (OF), and overlap with the clinically relevant part of the vessel (OT). We used the leave-one-out strategy to perform our experiments, by considering one of them as the target image, and the others as models.

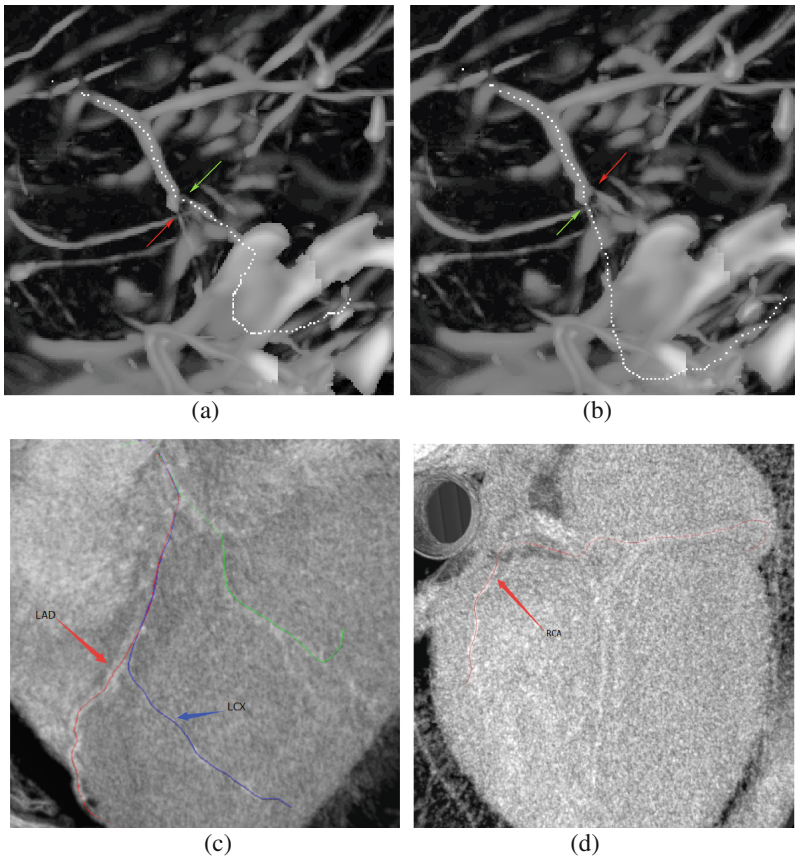


Fig. 3. Illustration of the coronary centerline extraction results: (a) is a maximal intensity projection (MIP) of the vesselness and the extracted centerline using the conventional method on the original vesselness images. The centerline goes into an undesired sub-branch due to the stenosis at a position of the main branch, which is pointed out by the red arrow. (b) is the MIP of the vesselness and the extracted centerline using the proposed method. The centerline is corrected and goes through the narrowed coronary artery thanks to the usage of the proposed filter and MMP method. (c) and (d) are the volume rendering results of a CTA image with extracted coronary centerlines. (Color figure online)

Figure 3 first provides an illustration of the coronary centerline extraction results. The CTA image has an indistinct segments of the coronary artery due to the stenosis. The conventional fast marching hence is prone to trace into the sub-branch which has no narrowed lumen, as the maximal intensity projection (MIP) image shows. By contrast, with the proposed filter, the indistinct vessel segment can be enhanced, helping the fast marching algorithm to pass the stenotic segment of the artery. Figure 3(b) provides the MIP of the vesselness and the extracted centerline result using the proposed filter and MMP method. Figure 3(c) and (d) visualize the volume rendering results of a CTA image with extracted coronary centerlines for demonstration.

Table 1 provides the results of the four measures and their scores by the proposed MMP. For comparisons, we also evaluated the coronary tracking using the original single model-guided single resolution MP [8, 9], referred to as MP in Table 1. Finally, to further investigate the robustness of the MMP, we deformed the coronary models and offset the detected ostia using random deformation and displacements, to simulate the MMP coronary tracking with less accurate registration and ostium detection. For each target centerline extraction, we simulated ten sets of deformations and offsets, resulting in eighty coronary extraction cases. Both the magnitudes of the deformation fields were set to less than the maximum errors we expected, for example the maximal displacement for offsetting the detected ostia was about 2 mm. The results of this study, referred to as SimuMMP, is presented in Table 1. Finally, the computation time for a MMP was about 1.6 min at the low resolution of $1 \times 1 \times 1$ mm and 3.4 min at the original resolution with the constraint mask from the previous result. This compares with 9.8 min by the conventional model-guided MP.

Table 1. The standardized scores of the coronary artery extraction by the proposed MMP, the conventional MP (MP), and the results of the simulated data by the MMP (SimuMMP).

OV	MMP		MP		SimuMMP		OF	MMP		MP		SimuMMP	
	%	Score	%	Score	%	Score		%	Score	%	Score	%	Score
RCA	84.6	48.4	73.3	38.7	87.6	49.2		60.7	42.6	57.3	38.4	60.0	41.1
LAD	64.2	33.0	39.2	20.3	67.8	34.9		39.2	26.9	24.2	14.1	34.6	24.0
LCX	70.1	41.5	45.6	25.2	63.0	37.3		50.7	35.7	46.2	34.0	51.8	38.7
Mean	72.9	41.0	52.7	28.0	72.7	40.5		50.2	35.1	42.6	28.8	48.8	34.6
OT	MMP		MP		SimuMMP		AI	MMP		MP		SimuMMP	
	%	Score	%	Score	%	Score		mm	Score	mm	Score	MM	Score
RCA	88.8	63.2	87.1	57.6	90.5	60.3		0.54	25.4	0.54	25.5	0.54	25.6
LAD	67.3	39.9	45.2	23.5	70.4	40.8		0.51	29.2	0.61	26.5	0.50	28.9
LCX	73.2	37.2	55.6	29.9	66.8	37.0		0.48	29.7	0.56	27.3	0.52	28.3
Mean	76.4	46.8	62.4	37.0	75.9	46.0		0.51	28.1	0.57	26.5	0.52	27.5

5 Conclusions

In this work, we have presented a new automatic method for extracting coronary centerlines, combining multi-model and multi-resolution within the MP framework, referred to as MMP. The multi-resolution is achieved using the new image filter which

can generate low resolution coronary images while preserving the salient vessel features and enhancing the vesselness for fast and robust vessel tracking. MMP achieved 72.9 % overlap score and 0.51 mm AI accuracy, which are evidently better than 52.7 % and 0.57 mm by the conventional model-guided MP. In conclusion, the proposed MMP is efficient and effective in coronary centerline tracking and can be valuable in clinics for coronary disease analysis using cardiac CTA. For the future work, we will apply the method to more test cases from our hospital as well as the publically available data to validate the performance.

Acknowledgment. This work was partially supported by the Chinese NSFC research fund (81301283), the NSFC-RS fund (81511130090).

References

1. Schaap, M., Metz, C.T., van Walsum, T., van der Giessen, A.G., Weustink, A.C., Mollet, N. R., Dikici, E.: Standardized evaluation methodology and reference database for evaluating coronary artery centerline extraction algorithms. *Med. Image Anal.* **13**(5), 701–714 (2009)
2. Zhu, N., Chung, A.C.: Minimum average-cost path for real time 3D coronary artery segmentation of CT images. In: Fichtinger, G., Martel, A., Peters, T. (eds.) MICCAI 2011, Part III. LNCS, vol. 6893, pp. 436–444. Springer, Heidelberg (2011)
3. Deschamps, T., Cohen, L.D.: Minimal paths in 3D images and application to virtual endoscopy. In: Vernon, D. (ed.) ECCV 2000. LNCS, vol. 1843, pp. 543–557. Springer, Heidelberg (2000)
4. Wink, O., Frangi, A., Verdonck, B., Biergever, M., Niessen, W.: 3D MRA coronary axis determination using a minimum cost path approach. *Magn. Reson. Med.* **47**(6), 1169–1175 (2002)
5. Kaul, V., Yezzi, A., Tsai, Y.: Detecting curves with unknown endpoints and arbitrary topology using minimal paths. *IEEE Trans. Pattern Anal. Mach. Intell.* **34**(10), 1952–1965 (2012)
6. Zheng, Y., Tek, H., Funka-Lea, G.: Robust and accurate coronary artery centerline extraction in CTA by combining model-driven and data-driven approaches. In: Mori, K., Sakuma, I., Sato, Y., Barillot, C., Navab, N. (eds.) MICCAI 2013, Part III. LNCS, vol. 8151, pp. 74–81. Springer, Heidelberg (2013)
7. Zheng, Y., Tek, H., Funka-Lea, G., Zhou, S., Vega-Higuera, F., Comaniciu, D.: Efficient detection of native and bypass coronary ostia in cardiac CT volumes: anatomical vs. pathological structures. In: Fichtinger, G., Martel, A., Peters, T. (eds.) MICCAI 2011, Part III. LNCS, vol. 6893, pp. 403–410. Springer, Heidelberg (2011)
8. Liu, L., Shi, W., Rueckert, D., Hu, M., Ourselin, S., Zhuang, X.: Coronary centerline extraction based on ostium detection and model-guided directional minimal path. In: 2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI), pp. 133–136. IEEE (2014)
9. Liu, L., Shi, W., Rueckert, D., Hu, M., Ourselin, S., Zhuang, X.: Model-guided directional minimal path for fully automatic extraction of coronary centerlines from cardiac CTA. In: Mori, K., Sakuma, I., Sato, Y., Barillot, C., Navab, N. (eds.) MICCAI 2013, Part I. LNCS, vol. 8149, pp. 542–549. Springer, Heidelberg (2013)
10. Kim, S.: An $O(N)$ level set method for eikonal equations. *SIAM J. Sci. Comput.* **22**(6), 2178–2193 (2001)

11. Zhuang, X., Rhode, K., Razavi, R., Hawkes, D.J., Ourselin, S.: A registration-based propagation framework for automatic whole heart segmentation of cardiac MRI. *IEEE Trans. Med. Imaging* **29**(9), 1612–1625 (2010)
12. Frangi, A.F., Niessen, W.J., Hoogeveen, R.M., Van Walsum, T., Viergever, M.A.: Model-based quantitation of 3-D magnetic resonance angiographic images. *IEEE Trans. Med. Imaging* **18**(10), 946–956 (1999)
13. Tang, H., van Walsum, T., van Onkelen, R.S., Hameeteman, R., Klein, S., Schaap, M., van Vliet, L.J.: Semiautomatic carotid lumen segmentation for quantification of lumen geometry in multispectral MRI. *Med. Image Anal.* **16**(6), 1202–1215 (2012)
14. Cohen, L.D., Kimmel, R.: Global minimum for active contour models: a minimal path approach. *Int. J. Comput. Vis.* **24**(1), 57–78 (1997)
15. Metz, C., Schaap, M., van Walsum, T., van der Giessen, A., Weustink, A., Mollet, N., Niessen, W.: 3D segmentation in the clinic: a grand challenge II-coronary artery tracking. *Insight J.* **1**(5), 1–6 (2008)
16. Zhuang, X., Shen, J.: Multi-scale patch and multi-modality atlases for whole heart segmentation of MRI. *Med. Image Anal.* **31**, 77–87 (2016)
17. Zhuang, X., Bai, W., Song, J., Zhan, S., Qian, X., Shi, W., Rueckert, D.: Multiatlas whole heart segmentation of CT data using conditional entropy for atlas ranking and selection. *Med. Phys.* **42**(7), 3822–3833 (2015)
18. Yatziv, L., Bartsaghi, A., Sapiro, G.: $O(N)$ implementation of the fast marching algorithm. *J. Comput. Phys.* **212**(2), 393–399 (2006)