Two Point Minimum Cost Path Approach for CTA Coronary Centerline Extraction

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Abstract

In this work a minimum cost path approach is adopted to extract coronary artery centerlines from CTA data. The algorithm depends on the manual definition of the start and end point of the vessel. The cost image used in the minimal cost path approach is based on a vesselness measure and a smooth window function on intensity. In the majority of the cases the method was able to extract the centerlines successfully (overlap > 90%). Accuracy of the method is around two times the voxelsize of the datasets. To conclude, minimum cost path approaches have potential for coronary artery centerline extraction, but improvements, especially regarding the accuracy of the method, still need investigations.

Contents

1 Introduction

For the evaluation of coronary arteries in computed tomography angiography (CTA) data, visualization techniques, such as maximum intensity projection (MIP), multi-planar reformatting (MPR), curved planar reformatting (CPR) and volume rendering techniques (VRT) are used in clinical practice [1]. MPRs and

CPRs are mainly determined from manually annotated coronary artery centerlines. The manual definition of these centerlines is generally performed on differently oriented projections of the CTA data and is a laborious task. Reliable (semi-)automatic coronary artery centerline extraction is therefore relevant in clinical practice. Furthermore, vessel centerlines can serve as a starting point for automatic quantitative vascular image analysis such as stenosis grading and measuring calcium volume.

Several authors proposed the use of minimum cost path approaches to solve the problem of vessel centerline extraction [4, 6, 8–11]. These approaches need at least the start and end point of the vessel, but additional user-interaction can easily be integrated to guide the centerline extraction in difficult cases (*e.g.* the presence of severe pathology or decreased image quality).

Wink et al. [10] explored different methods to determine the minimum cost path through a pre-defined cost image, for the extraction of vessel centerlines from medical image data. Among them are Dijkstra's algorithm [2], the A* algorithm [7], which makes use of additional heuristics to steer the search process, and wave front propagation analysis [9]. In [8], Wink et al. applied Dijkstra's algorithm for the extraction of coronary vessel centerlines from 3D MRA data. Olabarriaga et al. [6] applied a minimum cost path technique for the extraction of coronary artery centerlines from CTA data, but in this work the method was only evaluated on small vessel segments. Furthermore, Li et al. [4] and Wink et al. [11] proposed minimum cost path techniques in which scale is included as an additional dimension in the cost image. In these approaches scale selection is implemented in an implicit way, which is more robust compared to a more traditional explicit selection procedure. This can especially be an advantage in 2D images with overlapping vessel structures.

This work is carried out in the context of the workshop '3D segmentation in the clinic: A grand challenge II' at MICCAI 2008 [5]. It follows the approach of Wink et al. [8] and Olabarriage et al. [6], but a modified cost function based on intensity and a vesselness measure is used. Furthermore, the scale parameter for the vesselness computation is optimized using the training data of the challenge.

In the next section the outline of the method is presented. In section 3 the optimization procedure and evaluation experiments and their results are outlined. The last section of this paper contains a discussion on the results and the conclusion of this work.

2 Method

The problem of finding the coronary arteries in CTA data can be defined as finding the correct three-dimensional path through the data that follows the vessel of interest between its start and end point. In this work, a minimum cost path approach using Dijkstra's algorithm [2] is adopted to find this path between a manually defined start and end point. Resulting extracted centerlines are spatially smoothed using a Gaussian kernel (σ=1 mm), to decrease the effect of the discrete nature of the minimum cost path approach.

The cost image that is used in the minimum cost path approach is based on a priori information about coronary shape and intensity in CTA images. Vessels in CTA images are expected to appear as bright tubular structures in a darker environment and a vesselness measure is used to derive a measure for this tubularity [3]. This vesselness measure is defined as:

$$V(\vec{x},\sigma) = \begin{cases} 0 & \text{if } \lambda_2 \geq 0 \text{ or } \lambda_3 \geq 0 \\ \left[(1-\exp\left(-\frac{{R_A}^2}{2\alpha^2}\right)\right]\exp\left(-\frac{{R_B}^2}{2\beta^2}\right)\left[1-\exp\left(-\frac{R_S^2}{2c^2}\right)\right] & \text{otherwise} \end{cases} \tag{1}$$

with

$$R_A = \frac{\lambda_2}{\lambda_3} \qquad R_B = \frac{|\lambda_1|}{\sqrt{\lambda_2\lambda_3}} \qquad R_S = \sqrt{(\lambda_1)^2+(\lambda_2)^2+(\lambda_3)^2}$$

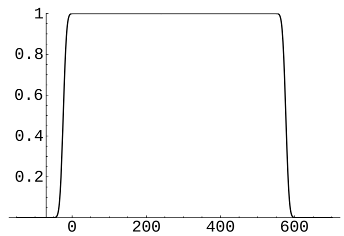


Figure 1: Example of intensity transformation function as given by equation (2) for $a_1 = -24$ HU, $a_2 = 576$ HU and $b = 0.1$.

(a) Input image (b) ROI (c) Vesselness (d) Intensity (e) Cost image

Figure 2: Example showing the results of the vesselness and intensity measure and the cost image derived from these two measures.

and $|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$ the eigenvalues of the Hessian matrix computed at scale σ. Frangi et al. [3] include this Hessian analysis in a multi-scale framework, but in this work only one scale is used.

Although the norm of the Hessian matrix in the third term of equation (1) gives a measure for local contrast, it does not differentiate between the occurrence of this contrast in high or low intensity regions. To ensure that bronchi and calcified regions will have high cost values, intensity is included as a second feature in the computation of the cost image. This is achieved by using the product of two Gauss error functions acting as a smooth window function (see also Figure 1):

$$T(\vec{x}) = \frac{1}{2}(\mathrm{erf}[b(I(\vec{x}) - a_1)] + 1)(1 - \frac{1}{2}(\mathrm{erf}[b(I(\vec{x}) - a_2)] + 1)) \tag{2}$$

with $I(\vec{x})$ the intensity of the input image at voxel position $\vec{x}$ and a_1, a_2 and b parameters to control the steepness and center of the two error functions.

Combining the vesselness and intensity measure, the final cost image is defined as:

$$C(\vec{x}, \sigma) = \frac{1}{V(\vec{x})\, T(\vec{x}, \sigma) + \varepsilon} \tag{3}$$

where ε is a small positive value introduced to avoid singularity of the function when $V(\vec{x})\, T(\vec{x}, \sigma)$ approaches zero.

3 Experiments and results

3.1 Parameters

The parameters for the intensity transformation function (equation (2)) were experimentally determined using the eight training datasets. Resulting settings are $a_1 = -24$ HU, $a_2 = 576$ HU and $b = 0.1$. These

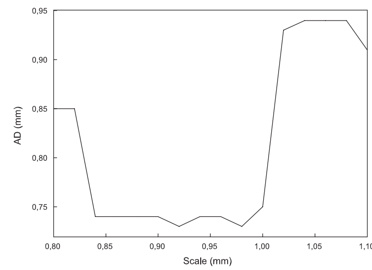


Figure 3: AD values for different scales used to optimize the vesselness measure.

settings include the range of intensity values corresponding to the contrast enhanced lumen, but exclude the bronchi and calcium intensity values. The scale parameter for the vesselness computation was optimized using the eight training datasets. The optimization was carried out in two steps. In the first steps scales between 0.8 mm and 1.5 mm (with stepsize 0.1 mm) were tested and in the second step, fine steps of 0.02 mm were taken around the optimal values of the first step. Optimization was performed using the AD measure and results of the second step can be found in Figure 3. The optimum was found at 0.92 mm, which was subsequently used in the experiments on the testing data. Other parameters for the vesselness computation were chosen as proposed by Frangi et al. [3].

3.2 Evaluation

Evaluation of the method was performed on the 16 testing datasets using the evaluation framework as described in [5]. Centerline extraction was performed between the start point (point S) and end point (point E) of the vessels. Results can be found in Table 1, 2 and 3. Examples of correctly extracted coronary artery centerlines can be found in Figure 4.

Table 1: Average overlap per dataset

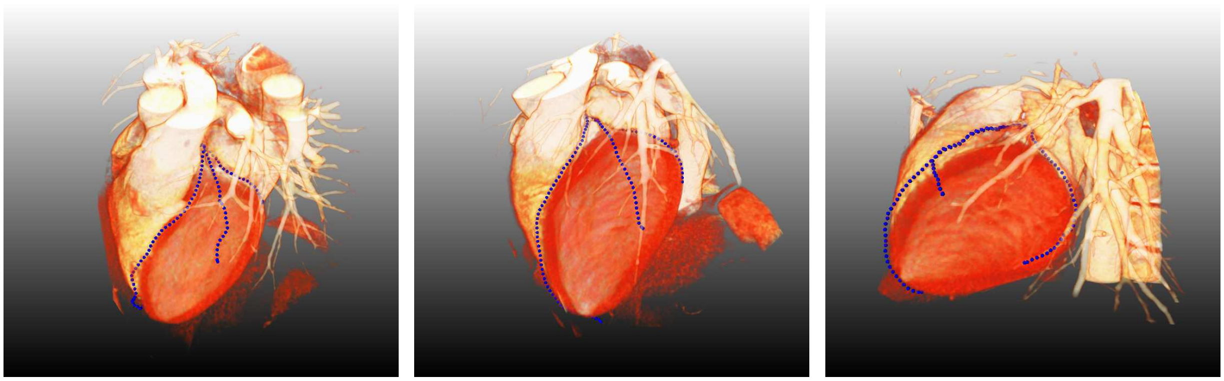
Dataset nr.	OV %	OV score	OV rank	OF %	OF score	OF rank	OT %	OT score	OT rank	Avg. rank
8	84.5	46.3	–	49.0	35.9	–	85.7	43.0	–	–
9	71.4	54.2	–	53.4	41.1	–	73.1	49.1	–	–
10	97.3	64.8	–	57.9	41.6	–	97.4	61.2	–	–
11	81.1	42.0	–	25.1	25.5	–	81.1	42.7	–	–
12	94.2	52.2	–	25.8	14.4	–	96.4	48.5	–	–
13	98.6	78.1	–	76.6	63.3	–	99.7	87.4	–	–
14	93.1	47.1	–	37.2	21.7	–	93.0	46.5	–	–
15	94.6	77.0	–	85.8	68.8	–	95.3	72.7	–	–
16	90.0	57.8	–	49.3	37.4	–	92.1	58.6	–	–
17	87.2	67.2	–	49.6	53.8	–	87.2	57.8	–	–
18	96.9	86.3	–	81.1	78.2	–	96.9	85.9	–	–
19	97.9	81.4	–	70.2	61.9	–	97.9	74.0	–	–
20	87.8	54.2	–	32.9	17.9	–	87.7	44.0	–	–
21	95.9	85.6	–	96.2	95.4	–	98.9	87.0	–	–
22	98.5	74.3	–	54.7	52.4	–	98.4	74.2	–	–
23	96.0	79.0	–	68.4	59.4	–	96.0	73.0	–	–
Avg.	**91.6**	**65.5**	**–**	**57.1**	**48.1**	**–**	**92.3**	**62.8**	**–**	**–**

Table 2: Average accuracy per dataset

Dataset nr.	AD mm	AD score	AD rank	AI mm	AI score	AI rank	AT mm	AT score	AT rank	Avg. rank
8	0.70	33.4	–	0.41	35.9	–	0.68	34.1	–	–
9	9.45	21.0	–	0.43	29.4	–	9.39	21.5	–	–
10	0.47	24.0	–	0.45	24.6	–	0.48	23.3	–	–
11	2.67	22.9	–	0.58	26.8	–	2.67	22.8	–	–
12	0.47	23.8	–	0.43	24.6	–	0.47	24.1	–	–
13	0.34	35.1	–	0.32	35.5	–	0.32	35.3	–	–
14	0.65	29.8	–	0.55	31.3	–	0.66	29.3	–	–
15	0.65	25.9	–	0.45	27.2	–	0.66	26.2	–	–
16	0.58	24.5	–	0.43	26.7	–	0.59	24.1	–	–
17	0.99	39.5	–	0.48	38.7	–	0.99	39.5	–	–
18	0.50	25.1	–	0.43	25.7	–	0.50	25.1	–	–
19	0.61	28.8	–	0.58	29.2	–	0.61	28.8	–	–
20	0.71	30.0	–	0.44	33.8	–	0.71	30.0	–	–
21	0.55	21.8	–	0.43	22.7	–	0.46	22.6	–	–
22	0.87	19.1	–	0.85	19.3	–	0.89	18.5	–	–
23	0.54	27.2	–	0.45	28.0	–	0.54	27.2	–	–
Avg.	**1.30**	**27.0**	**–**	**0.48**	**28.7**	**–**	**1.29**	**27.0**	**–**	**–**

Table 3: Summary

Measure	% / mm min.	% / mm max.	% / mm avg.	score min.	score max.	score avg.	rank min.	rank max.	rank avg.
OV	3.1%	100.0%	91.6%	1.6	100.0	65.5	–	–	–
OF	0.0%	100.0%	57.1%	0.0	100.0	48.1	–	–	–
OT	3.1%	100.0%	92.3%	1.5	100.0	62.8	–	–	–
AD	0.29 mm	36.17 mm	1.30 mm	1.2	52.1	27.0	–	–	–
AI	0.28 mm	1.09 mm	0.48 mm	10.7	48.7	28.7	–	–	–
AT	0.29 mm	36.18 mm	1.29 mm	1.2	52.1	27.0	–	–	–
Total							**–**	**–**	**–**



(a) Dataset 08 (b) Dataset 13 (c) Dataset 20

Figure 4: Examples of correctly extracted coronary artery centerlines.

3.3 Running time

Time needed to compute the cost image and perform centerline extraction for all four coronary arteries is approximately three minutes per dataset.

4 Discussion and conclusion

In this work a minimum cost path approach is adopted to extract coronary artery centerlines from CTA data. In the majority of the cases the method was able to extract the centerlines successfully. In only two cases the method failed and followed the incorrect vessel. Badly defined costs due to the presence of pathology or imaging artifacts for a part of the vessel of interest and a substantial difference in vessel lengths caused the integrated costs along the path through the incorrect vessel to be smaller than the integrated costs along the vessel centerline of interest. This problem may be solved by allowing additional user interaction by means of clicking an extra point in the correct vessel or by a better definition of the cost image. In all other cases the method was able to extract over 90% of the vessel centerline correctly. Accuracy of the method is around two times the voxelsize of the datasets. The method may be improved by using a multiscale approach for the computation of the vesselness measure, which is expected to better align the centerlines in parts of the vessels where the diameter is relatively large. The accuracy of the method might also be improved by a post-processing step that incorporates local image information to better align the extracted path with the center of the lumen. To conclude, minimum cost path approaches have potential for coronary artery centerline extraction, but improvements, especially regarding the accuracy of the method, still need investigations.

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