A Neighbourhood Search Feedback for Coronary Artery Centerline Tracking

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Abstract

Minimal user interaction in coronary artery centerline extraction is important for computer aided system in Coronary Artery Disease detection. However, manual seeding leads to error propagation most of the time. In this paper, we propose a neighbourhood search feedback mechanism in centerline tracking to overcome this problem. Two contributions from this paper are: (1) Seed Point Optimization where the defined seed point is optimized before tracking is initialized and (2) Backward-Forward Correlation Verification to verify the points before propagate in the tracking process. We evaluate the proposed method using publicly available dataset and demonstrate the results quantitatively and qualitatively. The experimental results demonstrate the reduction in error propagation by our proposed method compare with the method without feedback mechanism.

1 Introduction

Heart diseases are among the leading causes of death in the world, especially in developed countries and the Coronary Artery Disease (CAD) is the one that comprise the largest proportion. CAD is due to the occurrence of athesclerotic plaques in the coronary arteries and coronary artery calcification is part of the development of athesclerotic plaques which progressively narrow the arterial lumen and affect normal blood flow [1]. Conventionally, the standard diagnostic of CAD is employing invasive angiography which put patients in high risk and the diagnostic is very costly. Recently, non-invasive Computed Tomography Angiography (CTA) has been widely used to diagnose CAD. The motivation of this work is to provide a tool which assist radiologists or cardiologists in detecting, grading and classified the stenosis from CTA.

There are several CTA visualization techniques used in clinical practice for coronary artery visualization, such as volume rendering, Maximum Intensity Projections (MIP) and Curved Planar Reformation (CPR). These techniques assist in analysis of vessels's condition, stenosis grading and classification for surgical planning. Thus, obtaining a reliable coronary artery centerline for CTA visualization is crucial.

There are many coronary artery centerline extraction algorithms proposed in [2], [3] and evaluated by standard framework [3]. The methods are categorized into automatic seeding and manual seeding. For automatic seeding [4], the aorta detection is required to detect arteries's root as seed point for tracking. However, there are risks of fail in vessel tracking if unable to locate the roots. Therefore, we decide to investigate manual seeding initialization. In this paper, in order to ease the seed point's initialization process, we use only one start point (i.e. proximal of vessel) per vessel.

Coronary artery centerline extractions are classified into skeleton-based and tracking-based approaches. Segmentation of vessel required for skeleton-based then morphology operations are performed to obtain the centerline. While tracking-based approach traces the vessel centerline without segmentation required. Our proposed method aims to investigate toward tracking-based approach to reduce the challenge from vessel segmentation. Minimum cost path algorithm is the most popular class in coronary artery centerline extraction. [5] and [6] extract the coronary artery centerline using minimum cost path function and show promising results. However, there are still minimum numbers of cases where the method failed in vessel tracking due to the challenges. The challenges of extracting coronary artery from CTA images are mentioned in paper [7].

Due to these challenges, the vessels tracking will fail when error propagated during tracking process. Learning-based approach was proposed in [8] to reduce errors; however the training process requires high computational power and a training model. Thus, we investigate a different concept which uses feedback mechanism to reduce error without training stage and model required. In this paper, we proposed a method of coronary artery centerline tracking with neighbourhood search feedback mechanism after seed point optimization.

In our evaluation part, two measures: the capability to track the vessel of reference standard (Ω_1) and average distance error (Ω_2) are calculated to evaluate the results quantitatively. The two measures are compared against the measures from method without feedback mechanism. Besides, we demonstrate our finding qualitatively in the experimental results section.

2 Methodology

The proposed method aims to overcome the problem of error propagation in vessel centerline tracking which caused by initial seeding and ineffective tracking solutions. The key notion is to provide a feedback mechanism in the likelihood function as a self-optimization algorithm. In all tracking-based vessel centerline tracking methods, three tracking factors are considered: traversing direction, jumping distance and vesselness value [9]. In our proposed method, we apply neighbourhood search as the traversing direction and jumping distance to track the next candidate by matching the vesselness correlation of proximity.

2.1 Image Preprocessing

Image preprocessing is performed to enhance the vessel's region and ensure that the vessel's property is robust for tracking process. The image preprocessing consists of two steps: 1) Vessel Enhancement and 2) Piecewise Segmentation.

2.1.1 Vessel Enhancement

The purpose of this step is to enhance the boundary of the contrast regions with the ultimate goal of vessel delineation. In CTA, vessels appear as bright 3D tubular structures surrounded by darker environment caused by the contrast agent which injects to patients. This prior information projects spherical or elliptical contrasted regions on each image planar. The second-order partial derivative of Gaussian image (G),

$$G" = \begin{bmatrix} G_{xx} & G_{xy} \\ G_{yx} & G_{yy} \end{bmatrix} \tag{1}$$

describes the second-order structure of local intensity. Thus we apply the Laplacian of Gaussian (LoG), trace of matric $G"$ to sharpen the regions of interest i.e. coronary arteries. The output from convolution of the image, I with LoG is given by:

$$V(x,y) = LoG * I(x,y). \tag{2}$$

2.1.2 Piecewise Segmentation

As aforementioned, the blood vessels are surrounded by dark background on images, the main objective of this step is to eliminate the vessels from dark background. Besides, calcification in vessels appear similar with bone structures, we solve this problem by normalizing the vessel property with two defined threshold values, *Non-artery* threshold value, T_{NA} and *Confident-artery* threshold value, T_{CA}. The output defined as:

$$V'(x,y) = \begin{cases} 1 & V(x,y) < T_{CA} \\ \frac{V(x,y)-T_{NA}}{T_{CA}-T_{NA}} & T_{CA} \leq V(x,y) \leq T_{NA} \\ 0 & Otherwise \end{cases} \tag{3}$$

V(x,y) less than 0 denote blood pool regions. Thus, we define T_{CA} = -900 as the lower bound of *V(x,y)* and T_{NA} = 30 as the upper bound of *V(x,y)* to extract vessels regions.

2.2 Centerline Tracking

We propose a method which applies a neighbourhood search to track the next candidate from previous point and a feedback mechanism by matching correlation of proximity. Given a volume of processed image, $V'(x,y,z)$ where z refer to the slices, the algorithm start with a seed point, S to generate a set of tree points, $T_i = \{T_0(x,y,z), T_1(x,y,z), T_2(x,y,z), \ldots T_{K-1}(x,y,z)\}$; K is the number of tree points.

2.2.1 Proximity for Neighbourhood Search

One of the challenges in vessel's centerline tracking is the disturbance from structures proximity. Thus, defining an adequate proximity for neighbourhood search is crucial in order to reduce surrounding noises. In this paper, we introduce three proximity radius for different purposes: 1) *Vessel proximity radius*, R_V which generally used for neighbourhood search, 2) *Non-vessel proximity radius*, R_{NV} which is incorporated in tracking loop as stopping criteria and 3) *Turning proximity radius*, R_T which determine the tracking direction. From the empirical tests, we conclude that R_{NV} must be $2 \times R_T$ and R_T must be $\frac{2}{3} \times R_V$. Thus, we fix R_V as 6 pixels length for low resolution dataset and 8 pixels length for high resolution dataset.

2.2.2 Seed Point Optimization

The optimization of seed point location is crucial in order to reduce possibility of error propagation from initial defined seed point. The seed point optimization is based on the assumption where vessels center pixel intensity is always higher than the surrounding pixel's intensity. Given a defined seed point, S, the optimized seed point,

$$OptS = \arg\max(\mathbf{b}V_N'(x,y,z)) \tag{4}$$

where $\mathbf{b}$ indicates the binary value corresponds to foreground ($\mathbf{b} = 1$) or background ($\mathbf{b} = 0$); N refer to the number of neighbourhood pixels within the circle proximity which centered by S with radius, R_V (defined in previous section). To initialize the tracking loop, $OptS$ is assigned as the first vessel's tree point, T_0*(x,y,z)*.

2.2.3 Minimum Cost Path Approximation

In the centerline tracking loop, the previous tree point, T_{k-1} propagated to the current slice as a reference location to approximate the current tree point, t_k. However, t_k is not optimized. By searching the minimum cost function of the vesselness value ($\vec{V}_{kN}$) and distance between t_k with the neighbourhood's pixels of the proximity (D_{kN}), t_k is optimized as an approximated point by a weighted minimum cost function:

$$ApxT_k = \arg\min(\Phi\vec{V}_{kN} + \Psi D_{kN}) \tag{5}$$

where Φ and $\Psi \in$ [0,1] indicate the weighted coefficients in the minimum cost function. In our case, we consider $\vec{V}_{kN}$ and D_{kN} are equally significant, thus Φ and Ψ are set to 0.5. Herein, t_k is optimized as $ApxT_k$. Subsequently, verification step is proposed to reduce the error propagation in the following section.

2.2.4 Backward-Forward Correlation Verification

In this step, $ApxT_k$ will be verified by a modified Forward-Backward Correlation algorithm invented by Wang [10] which used to overcome the problem from traditional template-based tracking. Theoretically, the forward-backward correlation template-based tracking provides better accuracy in vessel's centerline tracking instead of point tracking as more information are investigated during the tracking process. Thus, we modify the algorithm which aim to verify the point's position by question the approximation, finding the best position in the reference location and locate again in the search region. We intend to utilize this concept to correct and verify the location of $ApxT_k$ from previous step. First, we perform a *backward-current* correlation correction for $ApxT_k$. Subsequently, the verification of final point is endorsed by a *forward-current* correlation matching algorithm.

In *backward-current* correlation correction, $ApxT_k$ is back propagate to the previous slice, $ApxT_{k-1}$ as the center point for a set of 4-tuples center points,

$$c^n_{k-1} = \prod_{n=0}^{4} ApxT_{k-1} + R_V * \omega(2\pi n/4) \qquad (6)$$

where $\omega(\theta) = \mathbf{u}\sin(\theta) + \mathbf{v}\cos(\theta)$; $\mathbf{u}$ and $\mathbf{v}$ denote a 2D plane. Each of search region is a circle proximity with radius, R_V. Correlation coefficients for each proximity region ($Region^n_{\mathbf{A}_{k-1}}$) are defined by

$$r^n_{\mathbf{A}_{k-1}} = \frac{\sum(\mathbf{A}^{N,n}_{k-1} - \overline{\mathbf{A}^n_{k-1}})(\mathbf{A}^N_k - \overline{\mathbf{A}_k})}{\sqrt{\sum(\mathbf{A}^{N,n}_{k-1} - \overline{\mathbf{A}^n_{k-1}})^2 \sum(\mathbf{A}^N_k - \overline{\mathbf{A}_k})^2}} \qquad (7)$$

where $\mathbf{A}$ represent $ApxT$. The matched region ($Region^{matched}_{A_{k-1}}$) is the proximity with maximum correlation coefficient and the corrected point is:

$$CorT_{k-1} = max(Region^{matched}_{k-1}(x,y,z)) \qquad (8)$$

Then in the *forward-current* correlation verification, $CorT_{k-1}$ is propagated forward to next slice, $CorT_k$ now as the center point for the set of 4-tuples center points,

$$c^n_k = \prod_{n=0}^{4} CorT_k + R_V * \omega(2\pi n/4) \qquad (9)$$

The correlation coefficients calculated by,

$$r^n_{\mathbf{C}_k} = \frac{\sum(\mathbf{C}^{N,n}_k - \overline{\mathbf{C}^n_k})(\mathbf{C}^N_{k-1} - \overline{\mathbf{C}_{k-1}})}{\sqrt{\sum(\mathbf{C}^{N,n}_k - \overline{\mathbf{C}^n_k})^2 \sum(\mathbf{C}^N_{k-1} - \overline{\mathbf{C}_{k-1}})^2}} \qquad (10)$$

where $\mathbf{C}$ represent $CorT$. Hence, the verified point is defined as:

$$VerT_k = max(Region^{matched}_k(x,y,z)) \qquad (11)$$

There are cases where more than one $VerT_k$ occurs. The last obtained point is accepted as $VerT_k$. Nevertheless, this does not affect much in our algorithm, merely small proximity region is defined. Finally, $VerT_k$ is collected as $T_k(x,y,z)$.

2.2.5 Tracking Scheme and Stopping Criteria

In order to track a 3D tubular structure, we include the direction examination to control the propagation direction using similar concept in correlation neighbourhood search. $2 \times \mathbf{n}$ number of correlation coefficients are calculated i.e. $\mathbf{n}$ from previous slice and $\mathbf{n}$ from next slice. Then the slice with maximum correlation coefficient is considered as the propagation direction. Consequently, the Minimum Cost Path Approximation is performed on the slice follow by Backward-Forward Correlation Verification. The

Algorithm: Feedback Mechanism of Tracking Framework
Input: CTA image, one initial seed point
Output: Coronary artery tree points
while *Distance* $\leq R_{NV}$ **do**
  Get points from Upward and Downward direction using proximity neighbourhood search;
  Get Distance of previous point and next predicted point in Downward direction;
  if *Distance* $> R_T$ **then**
    Predict point from Upward direction using Minimum Cost Path Approximation;
  else
    Predict point from Downward direction using Minimum Cost Path Approximation;
  Verify point using Backward-Forward Correlation Verification;
Finish tracking;

tracking process loops until the distance between two consecutive T more than a defined threshold R_{NV} and not background pixels. The details of feedback mechanism tracking steps are presented as above.

For multiple vessels tracking, a list of S are put in the queue and the algorithm is repeated iteratively.

3 Experimental Results and Evaluations

We evaluate the performance of proposed method on the datasets publicly available. 16 dataset are selected from the database. The CTA dataset are acquired with average resolution of 0.37mm x 0.37mm x 0.42mm. Three major coronary arteries were selected from each dataset for evaluation: left anterior descending (LAD), left circumflex (LCX) and right coronary artery (RCA).

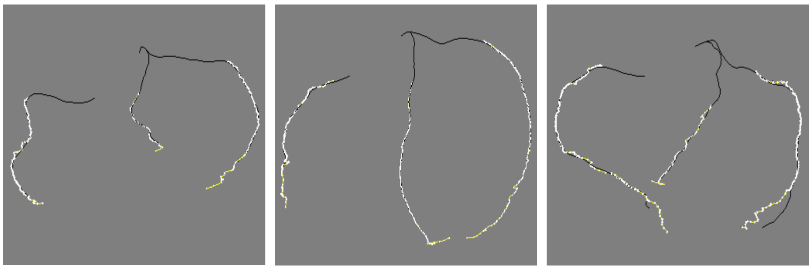
Two measures are used to evaluate the error propagation reduction by the estimated centerline from proposed method: (1) Ω_1 define as the capability to track the vessel of reference standard and (2) Ω_2 is the average distance error of the estimated centerline from reference standard. Our reference standard refer to the centerlines prepared by paper [11]. The points from proposed method are pair with points from reference standard using shortest Euclidean distance. Then the pair of points are sampled densely with distance less than or equal to 4 pixels length ($\approx$ 1.5 mm). $\mathbf{TP_m}$ defined as the points of estimated centerline points that have correspondence to reference standard; $\mathbf{TP_r}$ defined as the points of reference standard centerline points that have correspondence to estimated centerline; **FP** defined as the points of estimated centerline that do not have correspondence to reference standard; **FN** defined as the points of reference standard that do not have correspondence to estimated centerline.

Two evaluation measures are calculated:

$$\Omega_1 = \frac{\mathbf{TP_m} + \mathbf{TP_r}}{\mathbf{TP_m} + \mathbf{TP_r} + \mathbf{FP} + \mathbf{FN}} \times 100\% \qquad (12)$$

$$\Omega_2 = \frac{\mathbf{TotalDist}}{\mathbf{TotalPts}} \qquad (13)$$

where **TotalDist** indicates the total distance error between estimated centerline and reference standard and **TotalPts** refers to the total number of sampled points from estimated centerline. We compare the results from proposed method and minimum cost path vessel tracking without feedback mechanism (NFM) to evaluate the capability of the proposed method in error propagation reduction. Note that the minimum cost path vessel tracking without feedback mechanism method is implemented based on the minimum cost path function in our Minimum Cost Path Approximation module (in section 2). Table 1 shows the experimental results. Figure 1 illustrates the results from our proposed method tested with 3 different dataset.



(a) Dataset 1 (b) Dataset 2 (c) Dataset 3

Figure 1. Overlay of estimated centerline from proposed method in white color and reference standard in black color from 3 dataset. [Best viewed in color.]

Table 1. Experimantal Results.

Measures	*NFM*			*Proposed Method*		
	Min	**Max**	**Average**	**Min**	**Max**	**Average**
Ω_1 (%)	3.3	92.4	50.0	22.7	88.5	67.6
Ω_2 (mm)	0.33	1.04	0.57	0.31	0.81	0.52

Refer to Table 1, our proposed method improves Ω_1 (capability to track the vessel of reference standard) by 17.6% and reduces Ω_2 (average error distance) by 0.5mm compare with NFM. In Figure 1, the reference standard superimposes estimated centerline (proposed method) for each dataset to illustrate the proficiency of our proposed method compare with reference standard; white lines indicates estimated centerlines from proposed method and black lines indicates reference standard. Notice that, the initial points of our proposed method are not defined from the beginning of the coronary artery, because our proposed method still not able to cope with line-like profile (not blob-like shape e.g. vessel's bifurcation) and vessel's branching problem due to the defined circle proximity for neighbourhood search. Thus, we define the seed points after the line-like profile in order to test the capability of proposed method in reducing error propagation.

4 Conclusion

We propose a neighbourhood search feedback mechanism for coronary artery centerline tracking using likelihood matching of proximity in order to reduce error propagation. The algorithm tested with 16 CTA dataset, the experimental results show that our proposed method improves 17.6% in capability to track vessel and reduces 0.05mm of average distance error compare with the method without feedback mechanism. These results provide evidence whereby the neighbourhood search feedback mechanism has the potential in reducing error propagation. However, modification of feedback mechanism is required for different tracking algorithm. Besides, improvement of algorithm is needed to enhance the feedback mechanism. For instance, extract difference feature for correlation verification.

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