Artery Skeleton Extraction Using Topographic and Connected Component Labeling

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Abstract

In this paper, we propose a method for the detection and extraction of coronary artery skeletons (centerlines) based on the morphologicalprocessing of the topographic features of coronary angiogram images.

Initially, the angiogram is pre-processed for noise reduction and artery enhancement through directional morphological filtering by reconstruction. The topographic features of the resulting image are detected based on first and second-order image derivatives which characterize the local differential image structure. Using an artery model of a smooth elongated object with an approximately Gaussian smoothed semi-elliptical profile, the candidate skeleton areas are detected as sets of points consisting of ridges, saddle points and peaks. False skeleton areas, produced due to the noise sensitivity of the differentiation filters, have small size and are eliminated by connected component labeling (CCL). CCL may cause the elimination of a few true skeletons which are recovered by the morphological operation of binary reconstruction.

Experimental results on clinical coronary angiograms are presented and discussed indicating the robust performance of the proposed method.

1. Introduction

Coronary angiographic images (angiograms) constitute the most reliable tool for diagnosing the presence of coronary artery disease, one of the greatest health problems in industrial countries. The development of automated image analysis techniques for objective and precise analysis of coronary angiograms is important to the clinical decision-making process in the treatment of patients with coronary disease. Most angiogram analysis techniques, interactive or not, initially extract the 2-D coronary artery skeleton [1]. The underlying model is based on the assumption that arteries are thin elongated objects and can be efficiently represented by their skeletons or centerlines. The existing skeleton extraction techniques are based on sequential tracking of user-defined artery segments or recursive tracking of the entire CAT starting from an initial artery point (e.g. ostium) [1,2]. The main disadvantage of these techniques is the requirement of user interaction in defining the artery segment of interest or initiating the arterial tree-tracking process. Also, a number of tracking parameters must be adjusted for achieving best results [1,3].

In our work, a novel method for the automated detection and extraction of the coronary artery skeletons from single-view angiograms is presented. A key idea of the proposed method is the assumption that the coronary artery skeletons are image point sets having certain differential properties. Specifically, the nature of the angiogram acquisition process allows the consideration of an angiogram as a surface of which certain topographic features, namely, ridges, peaks and saddle points, may be used to characterize elongated thin structures, such as arteries.

In Section 2, the directional morphological filtering techniques for angiogram noise reduction and arteries enhancement are presented. In Section 3, the detection and extraction method of coronary artery skeletons as digital planar curves is described in detail. Finally, in Section 4 experimental results from the application of the method to real coronary angiograms are shown and discussed.

2. Morphological preprocessing

The detection of various features in coronary angiograms, such as artery skeletons and borders, is a rather difficult task since angiograms are typically low contrast noisy images. In order to assist the subsequent feature detection techniques, such as topographic labeling or tracking, the angiogram noise must be reduced while the objects of interest, e.g. coronary arteries, must be preserved and enhanced. In addition, due to the presence of irrelevant anatomic structure, the highly non-uniform background must be simplified in order to reduce the image structure complexity which may limit the performance of the subsequent algorithms. In order to reduce noise and remove the irrelevant objects of non-linear shape, the

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supremum of directional openings at various directions with reconstruction is computed [4]. Specifically, let $I(i,j)$ be a Nr x Nm grayscale angiogram. The *directional dilation* and *erosion* of size N at direction d are defined as follows

$$\delta_{N,d}(I)(i,j) = \max_{B_{N,d}(k-i+Ns,\, l-j+Ns)=1} \{I(k,l)\},$$

$$\varepsilon_{N,d}(I)(i,j) = \min_{B_{N,d}(k-i+Ns,\, l-j+Ns)=1} \{I(k,l)\},$$

where $B_{N,d}$ is a linear structuring element of size N and direction d. The *directional opening* and *closing* of size N at direction d are defined as follows

$$\gamma_{N,d}(I) = \varepsilon_{N,d}(\delta_{N,d}(I)),$$

$$\phi_{N,d}(I) = \delta_{N,d}(\varepsilon_{N,d}(I)),$$

where $\delta_{N,d}$, $\varepsilon_{N,d}$ are the directional dilation and erosion operations of size N at direction d. The supremum (maximum) of directional openings of size N and number of directions k is defined as

$$\Gamma_{N,k}(I) = \max_{i=1,\dots,k}\{\gamma_{N,di}(I)\},$$

where the angle between linear structuring element of size N and direction d_i, $B_{N,di}$, $i=1,\dots,k$, with the horizontal axis is equal to 180i/k. The application of the supremum of directional openings to the angiogram I reduces noise and removes all objects which do not fit at least in one linear element. By assuming that the maximum artery width is W_M, our experiments showed that good results are achieved using linear elements of size W_M and number of directions $4*L$, where $W_M=2*L+1$. However, the application of $\Gamma(.)$ distorts the shape of the remaining objects. For this reason, the operation of *reconstruction by dilation* is applied using the original angiogram I as mask.

3. Skeleton extraction

3.1. Topographic labeling of image pixels

The computation of the image gradient and Hessian is based on estimates of the first and second-order partial derivatives at each image point, namely, I_x, I_y, I_{xx}, I_{yy}, *and* I_{xy}. The Hessian at each image point is a 2 x 2 real symmetric matrix. The eigenvalues λ_1, λ_2 are computed by solving the characteristic equation of H, whereas the eigenvectors ω_1, ω_2 are obtained by solving the corresponding 2 x 2 linear systems. Given the computed image derivatives required to assign topographic labels to the image pixels, the topographic label assignment rules (see [7]) are applied to each image pixel. However, due to the sampling grid used, a topographic feature may not coincide exactly with a pixel center. As a result, the gradient magnitude, or the inner product of the gradient vector with the eigenvectors, may not be equal to zero at the pixel center [5]. For this reason, the zero crossings of the first directional derivatives along the directions ω_1 and ω_2 are computed.

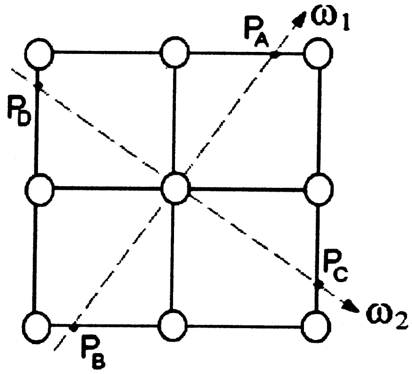

Figure 1: Detection of zero crossings to the eigenvector directions

The zero crossing computation procedure is illustrated in Figure 1. Eigenvector ω_1 intersects the image square grid at points P_A, P_B. The first directional derivative at direction ω_1 is computed at points P_A and P_B by calculating the inner product of the image gradient at these points with the vector ω_1. The image gradient at points P_A, P_B is calculated using linear interpolation. Pixel P may be a zero crossing in none of the directions ω_1, ω_2, in exactly one of the two directions or in both directions. If P is not a zero crossing in either ω_1, or ω_2, then P is a hillside point. If P is a zero crossing in *exactly* one of ω_1, and ω_2, then P is either a ridge point or a ravine point depending on the sign of the corresponding eigenvalue. If P is a zero crossing in *both* ω_1, ω_2, then P is peak or pit or saddle or ridge or ravine depending on the signs of the eigenvalues.

3.2. Connected component analysis of candidate skeleton regions

An image point is a *candidate* skeleton point if its topographic label belongs to the set {ridge, saddle, peak}. These points form elongated thin regions which, however, are not one pixel wide. Also, due to noise and irrelevant structures, a large number of false skeleton points are detected. In order to separate the true skeleton points from the false ones, each skeleton point p is assigned a weight (or height) equal to the difference of its original intensity $I(p)$ from the minimum intensity of its N_w x N_w square neighborhood, N_{Nw}. This operation is known as *morphological gradient by erosion*. The value of parameter N_w should be approximately equal to the diameter of the thickest artery. The resulting image W is processed to extract the true skeleton areas as follows. Initially, W is binary thresholded using a *high* and a *low* threshold, $T_h > T_l$, resulting in the images W_{Th} and W_{Tl}, respectively. Then, the connected components of W_{Th} are computed and those having size less than a predetermined threshold T_s are eliminated. Note that, an image region is defined as a connected component if for any pair of region pixels, there exists at least one path that connects them, consisting only of region pixels. The operation of identifying the connected components of an image is referred to as connected component labeling (CCL). CCL is computed by efficient linear time algorithms based on breadth-first image scanning using First-In-First-Out data structures (queues) [6]. The small-size component elimination operation is justified by the fact that, due to noise, false skeleton areas have small size while the true ones are of much greater size and, consequently, they survive the elimination process, at least partially.

Following the CCL stage, the image C is reconstructed using the image W_{Tl}, in order to recover the partially eliminated true skeleton areas. Reconstruction is accomplished through the morphological operation of *binary geodesic reconstruction by dilation* [6]. Specifically, the binary images W_{Tl} and C satisfy the relation $C \subset W_{Tl}$ in the sense that, for each pixel p, $C(p) = 1 \Rightarrow W_{Tl}(p) = 1$. C is called the *marker* image and the W_{Tl} is the *mask*. Let $W_{Tl}^{(1)}$, $W_{Tl}^{(2)} \ldots W_{Tl}^{(n)}$ be the n connected components of W_{Tl}. Then, the reconstruction $\rho_{W_{Tl}}(C)$ of W_{Tl} from C is the union of the connected components of W_{Tl} which contain at least a non-zero pixel of C. Finally, the reconstructed image is thinned in order to produce one-pixel wide skeleton curves.

4. Experimental results

Figure 2(left) shows a low-contrast 256 gray level, 512 x 512 coronary angiogram which was used in order to demonstrate visually the performance of the proposed algorithm in detecting the artery skeletons. At the preprocessing stage, the noise corrupting the angiograms was reduced using the supremum of directional openings with linear element size 21 and number of directions 8. Smaller values of the linear element size may produce noisy regions within the arteries of width larger than the linear element size. Larger values may cause decreased enhancement of the thin highly curved arteries. Figure 2(right) shows the result of the topographic labeling stage. Only the pixels with label in {ridge, saddle, peak} are shown (black). It is clear that, the pixels corresponding to artery skeletons are successfully detected as continuous thick curves.

However, due to noise and the various remaining anatomical objects in the angiogram, a large portion of the detected candidate skeleton points are false in the sense that they do not belong to artery skeletons. Figures 3 (left and right) show the binary thresholding and the small connencted component elimination result C, respectively. The high threshold was $T_h = 10$ and the size threshold T_s=30. The reconstruction by dilation result is shown in Figure 4 (Top) which through thinning results in the final skeletons (Figure 4 (Bottom)).

5. Experimental results

A detection and extraction method for coronary artery skeletons was presented based on the form of coronary artery projections resembling elongated smooth surfaces with approximately semi-elliptical cross sections. The proposed method uses the topographic features of the angiogram which is regarded as noisy sampling of the underlying smooth surface. The experimental results on coronary angiograms show the successful detection of skeletons of very low contrast arteries. However, due to structural noise, a significant portion of the detected skeletons does not correspond to coronary arteries. The detection and reduction of false skeletons is achieved by weighting the detected skeleton points based on their local height (intensity). Then, binary thresholding is applied, followed by small connected component detection and elimination, morphological reconstruction by dilation, and thinning.

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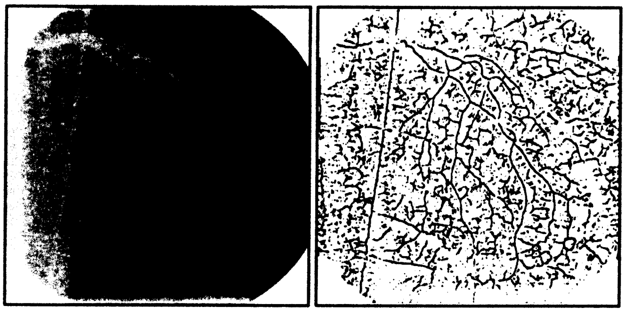

Figure 2 Left: Original coronary angiogram, Right: Detected Skeleton regions consisting of Ridges, Saddles and Peaks.

Figure 3 Left: Result of thresholding (high threshold), Right: Result of connected component elimination.

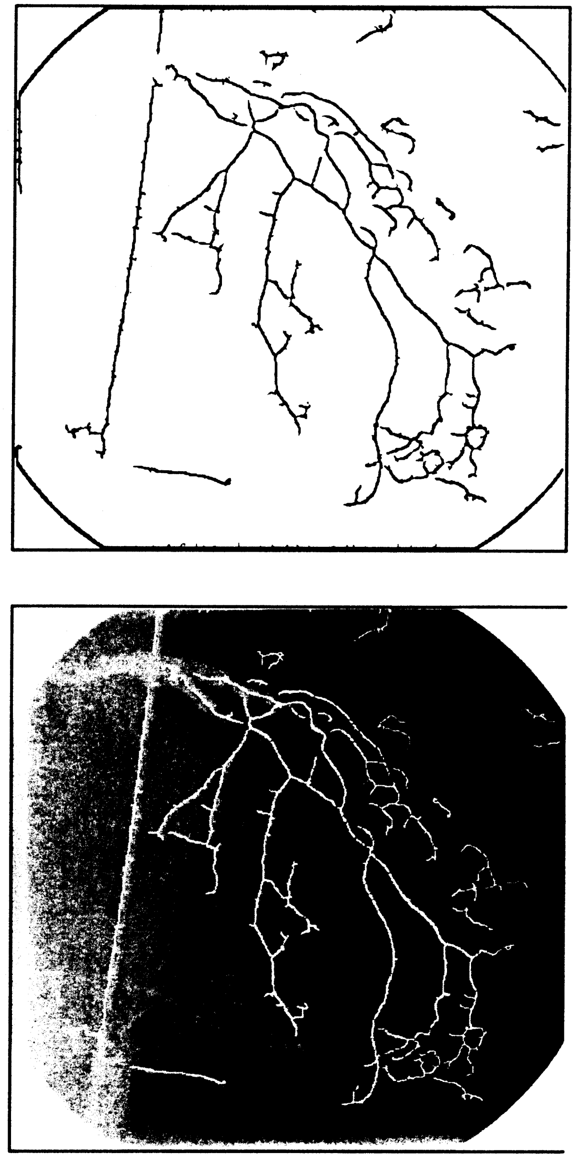

Figure 4 Top: Result of binary reconstruction by dilation Bottom: Thinned skeletons overlaid to the original image.

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