A Composite of Features for Learning-based Coronary Artery Segmentation on Cardiac CT Angiography

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Abstract. Coronary artery segmentation is important in quantitative coronary angiography. In this work, a novel method is proposed for coronary artery segmentation. It integrates coronary artery features of density, local shape and global structure into the learning framework. The density feature is the vessel’s relative density estimated by means of Gaussian mixture models and is able to suppress individual variances. The local tube shape of the vessel is measured with the advantages of the 3-dimensional multi-scale Hessian filter and is able to enhance the small vessels. The global structure feature is predicted from a support vector regression in terms of vessel’s spatial position and emphasizes the geometric morphometric attribute of the coronary artery tree running across the surface of the heart. The features are fed into a support vector classifier for vessel segmentation. The proposed methodology was tested on ten 3D cardiac computed tomography angiography datasets. It obtained a sensitivity of 81\%, a specificity of 99\%, and Dice coefficient of 84\%. The performance is good.

1 Introduction

In coronary heart disease (CHD), plaque builds up inside the coronary artery and results in narrowing of artery lumen and limitation of the blood supply to the heart muscle. CHD could lead to a life-threatening heart attack. Cardiac computed tomography angiography (CTA) is a commonly used non-invasive imaging modality for CHD diagnosis. Timely and correct diagnosis requires quantitative approaches to the angiographic evaluation of coronary anatomy, among which coronary artery segmentation is often one of the key elements. Automatic segmentation of coronary artery tree is challenging due to individual variances, vessel abnormalities of stenosis, calcification, and insufficient contrast agent, etc. A robust algorithm is required.

Feature selection is essential in vessel segmentation. On CTA images, the coronary artery appears hyperdense compared with the myocardium. Thus, the density is a straightforward feature for vessel segmentation. Kitslaar et al. [1] proposed to segment the coronary tree using a region growing scheme on the images with the heart
and aorta pre-segmented. Wang et al. [2] presented a fuzzy connectedness algorithm for the coronary artery segmentation. Automatic rib cage removal and ascending aorta tracing were included to initialize the segmentation. The density feature works well on large vessels of high contrast, but is not discriminative for tiny vessels of low-contrast. The local shape features, in the form of 3D tubular/cylinder structure or 2D cross-sectional template, are commonly used for vessel enhancement or shape constraints of segmentation. Li et al. [3] proposed to segment vessels using Hessian filters together with Gaussian filter based intensity compensation. Zhou et al. [4] proposed to extract coronary artery tree using multi-scale Hessian filter based vessel enhancement and a 3D dynamic balloon tracking. Yang et al. [5] improved the Frangi’s filter by suppressing step-edge responses. The improved filter was employed in a centerline extraction pipeline. Zambal et al. [6] proposed to match two small-scale cylinder-like models via depth-first search to extract the coronary artery tree. Schaap et al. [7] presented a vessel cross sectional segmentation using shape regression. Wong et al. [8] employed non-linear principal curves in vessel centerline detection and the vessels were modelled on cylinders along the polygonal lines. Schneider et al. [9] proposed to segment vessels using multivariate Hough voting and oblique random forests, with local image features extracted by steerable filters. Friman et al. [10] proposed a multiple hypothesis template of the vessels for tracking approach of small arteries. Generally, the local shape features/constraints mentioned in the above methods need an elaborate tracing scheme to complete the segmentation. To simplify the segmentation procedure, a global artery model was built in [11, 12]. Kitamura et al. [11] proposed to build the coronary shape model composed of 30 discrete nodes sampled from three major coronary arteries and two coronary veins. The shape model was then fitted to the detected candidates using a graph matching. Zheng et al. [12] proposed to generate a mean centerline model of the coronary arteries on 108 datasets and the model was employed to constrain the tracing of coronary arteries to detect. The good performance of those two methods indicated the helpfulness from the global structure information of coronary arteries, however, so far, few work has been reported on it.

In this work, we proposed a composite of features for coronary artery segmentation via a supervised learning framework. The composite features describe the coronary arteries’ properties of density, local shape, and global structure. A novel relative density feature is estimated using Gaussian mixture models and is able to suppress the individual variances. A local shape feature is measured via the 3D multi-scale Hessian filter to enhance small vessels. A new global structure feature is predicted from a support vector regression (SVR) in terms of vessel position and emphasizes the geometric morphometric attribute of the coronary artery tree running across the surface of the heart. This feature facilitates discriminating the coronary artery tree from other spurious structures. This method is different from the studies in [11, 12], where only the 3 main arteries were separately modelled. Our global structure feature describes the whole coronary tree, which is relatively robust to coronary variants. The composite features are fed into a support vector classifier (SVC) for vessel segmentation. The contributions of our work include (1) a general composite representation of the coronary tree, (2) a novel relative density feature, (3) a new global structure feature, and (4) the integration of composite features into a supervised learning framework.
2 Composite Features

2.1 Relative Density

The imaged vessel density varies due to individual variances or imaging protocols, as observed in the hyper-dense region in Fig. 1(a). An absolute density feature may not work well for all datasets. A relative one is better. On cardiac CTA, the visible tissues are bone, vessel, muscle, skin, fat etc. They form several peaks in the density histogram, which can be modelled by a Gaussian Mixture Model (GMM) [13]. Furthermore, we cropped the CTA images within the field of view of the heart, and the density peaks of the cropped images are similar to that of the original images. As shown in Fig. 1(b), the density centers of those peaks remain same while the counts decrease after cropping. Thus, it is possible for us to achieve a relative density representation consistent in appropriate ROIs, which is defined as the density ratio of vessels to its surrounding tissues, to deal with diverse images.

A GMM is a parametric probability density function represented as a weighted sum of Gaussian component densities:

\[ p(v|\theta) = \sum_{i=1}^{M} w_i \frac{1}{\sqrt{2\pi} \Sigma_i} \exp \left\{ -\frac{1}{2} (v - \mu_i) \Sigma_i^{-1} (v - \mu_i) \right\}, \]

where \( v \) is the density feature; \( M \) is the number of Gaussian components; \( \{w_i\}_{i=1}^{M} \) are the mixture weights, satisfying the constraint that \( \sum_{i=1}^{M} w_i = 1 \); \( \{\mu_i\}_{i=1}^{M} \) are the mean vectors and \( \{\Sigma_i\}_{i=1}^{M} \) are the covariance matrices. The complete GMM is parameterized by \( \theta = \{ w_i, \mu_i, \Sigma_i \}_{i=1}^{M} \). Here, \( M \) is empirically set a value of 4, since most of the datasets form four peaks in histogram as shown in Fig. 1. An iterative Expectation-Maximization (EM) algorithm [14] is used to estimate the parameters. If the Gaussian components are ranked in mean density from high to low, the relative density of a voxel is calculated as the ratio of its image density, \( v \), to the mean density values of the first two components, as shown in (1). The two components are usually the vessel’s neighbors which are close to vessels in terms of density or position.

\[ F^{RD} = \left\{ \frac{v}{\mu_1}, \frac{v}{\mu_2} \right\} \]

(1)
2.2 Local Shape Feature

Hessian matrix-based filter has been widely used in coronary artery segmentation [3-5]. A combination of the eigenvalues of the Hessian matrix [15], is adopted here to describe vessel’s shape locally. The local shape feature at a voxel is calculated as:

\[
F_{LS} = \begin{cases} 
\lambda_2 - \lambda_3, & \text{if } |\lambda_1| \leq |\lambda_2| \leq |\lambda_3|, \text{ and } \lambda_2, \lambda_3 < 0 \\
0, & \text{otherwise}
\end{cases}
\]  

(2)

where \(\lambda_1, \lambda_2, \lambda_3\) are the eigenvalues of the Hessian matrix. Multi-scale filtering scheme is also adopted to tackle vessels of various sizes, which is fulfilled by employing Gaussian smoothing with kernel size of \(\delta\) on the images before Hessian filtering. The upper limit of the coronary lumen diameter is 4.5mm, reported by Dodge et al. [16]. Thus, \(\delta\) is set as 1, 2, 3, 4 and 5 mm in this study. The maximum value among single scale filter responses is retained as local shape feature at this voxel.

2.3 Global Structure Feature

We proposed to model global spatial structure of the coronary tree using support vector regression (SVR) with radial basis function (RBF) kernel [17].

![Diagram](image_url)

**Fig. 2.** (a) the polar coordinates of a vessel voxel in a defined coordinate system XYZ, (b) an example of the global feature response map, (c) the artery regions have large responses (red)

**Input vector preparation.** To train a SVR, the input data has to be normalized. The coronary circulation is first introduced. The left and right coronary arteries originate at the root of the aorta, run on the surface of the heart and supply blood to the myocardium. The left coronary artery distributes blood to the left side of the heart, the left atrium and ventricle, and the interventricular septum. The right coronary artery proceeds along the coronary sulcus and distributes blood to the right atrium, portions of both ventricles, and the heart conduction system. The apex of the heart is the lowest superficial part of the heart, formed by the left ventricle and directed downward, forward, and to the left [16, 20]. According to the coronary artery anatomy, it can be observed that the aortic root and the heart apex are key points in coronary structure. Thus, the vector from aortic valve to the heart apex is defined as the reference vector to regularize the input data. In our work, the input vectors for SVR training are derived from the vessel’s polar coordinates as illustrated in Fig.2 (a). The reference vector’s direction is defined as the Z axis or polar axis and its length is written as \(\ell\). Given an image coordinate system \(X'Y'Z'\) with axis \(X'\) from right to left, \(Y'\) from posterior to anterior, and \(Z'\) from superior to inferior; a new coordinate system XYZ...
is established by rotating $X'Y'Z'$ an angle of $\alpha$ along the axis perpendicular to both $Z$ and $Z'$. In XYZ, the polar coordinates of a vessel voxel can be calculated as $\{\rho, \gamma, \phi\}$. Thus, the input vector of a training voxel is

$$x = (\rho/\ell, \gamma, \sin\phi, \cos\phi)$$

(3)

where the radial coordinate $\rho$ is normalized by $\ell$ for regularization on size. The angular coordinate $\gamma$ is directly used, while $\phi$ is represented as $\sin \phi$ and $\cos \phi$ to retain its periodical and continuous attributes.

Support vector regression. Given the input vectors and the corresponding target vectors, SVR is employed to model the global spatial structure using

$$f(x) = \sum_{i=1}^{N} \alpha_i \exp\left(-\frac{||x_i - x||^2}{2\sigma^2}\right) + b$$

(4)

where $N$ is the number of data points, and $x_i$ is the input vectors. The model is trained with the aid of SVM^\text{light} [18]. To select the optimized parameters for SVR, a k-fold cross-validation technique is used. Four training datasets are evenly divided into two groups. One group serves as training set and the other is used to test the model. Then, two groups exchange the roles in training and testing, and the experiments are conducted again. The parameters that minimize the average mean square error are selected. In this work, $\sigma$ is set as 7.1. Given a voxel with polar coordinates of $\{\rho, \gamma, \phi\}$, its global structure feature is predicted using the trained SVR as:

$$F^{G\delta} = f((\rho/\ell, \gamma, \sin\phi, \cos\phi))$$

(5)

The global feature is mainly designed to discriminate coronary arteries from other anatomical structures in terms of spatial position. It will highlight the vessels on the heart surface so as to remove the false positives, which are similar to coronary arteries in density and local shape, e.g. vessels in pulmonary circulation. An example of the global feature map was shown in Fig. 2(b), where voxels around the heart surface has relatively strong responses. When overlaid with the CTA images as shown in Fig. 2(c), the high response voxels were found covering regions the arteries run through.

3 Supervised Learning-based Segmentation

To train a supervised-learning based classifier, we first need to decide the training samples. For one CTA dataset, the $N^+$ positive samples are randomly selected from the labelled coronary arteries. The $N^\text{train}$ training datasets are evenly sampled and we have $N^\text{train} \times N^+$ positive samples in total. The negative samples are obtained for balance. Here, the negative data refers to image voxels except for the labelled coronary arteries. As described in section 2.1, one dataset was modelled using $M$ Gaussian components with regards to density, which represent various tissues for classifier to discriminate. Therefore, we randomly sample the negative data in the $M$ components respectively. The sample size in each component is the same $N^+ / M$. In this work, $N^+$ is set as 100 empirically. The composite features of the samples, $F = \{F^{RD}, F^{LS}, F^{G\delta}\}$, can be calculated using (1), (2), and (5). The aortic valve and the heart apex, for $F^{G\delta}$ computation, are manually located on the images by the user.

With the samples and their composite features obtained, a support vector classifier (SVC) is trained for coronary artery segmentation. In the classification problem using
SVC, the objective is to find a hyperplane that separate the classes with a maximized separation margin. In this work, a linear unbiased hyperplane was sought to separate the coronary arteries from other tissues.

To extract a connected coronary artery tree, a region growing scheme is employed on the output images from SVC, which starts growing from the aorta. The aorta appears hyperdense on cardiac CT angiography and can be segmented by an appropriate threshold. Here, the threshold is set as \( \mu_1 - \sum_1 \), where \( \mu_1 \) and \( \sum_1 \) are defined in Section 2.1. The upper limit of ascending aortic diameter is 42.6 mm reported by Mao et al. [19]. The angle of aortic insertion on the left ventricle is from 30 to 60 degrees [20]. Based on these statistics, a separation disc of 5cm in diameter is placed on the aortic valve to isolate the aorta from the left ventricle. The separation disc’s normal direction is along the polar axis Z defined in Section 2.3. The segmented aorta is superposed on the output images of the classifier to start the region growing.

4 Experimental Results and Discussion

Experimental results. After approval by the Institutional Review Board, ten anonymized cardiac CTA datasets, from ten CHD patients, were evaluated in this work. The CTA scans were acquired on a 320-row scanner (Aquilion ONE, Toshiba Medical System) in the National Heart Centre Singapore (NHCS) between May and July 2014. Diastolic reconstructions were used and the voxel size of the datasets was \((0.39 \pm 0.05) \times (0.39 \pm 0.05) \times 0.5\) mm\(^3\). Six datasets were randomly selected for training and the other four were used for testing. With the supervision from a cardiologist, an engineer manually labelled the aortic valve, the heart apex, and the coronary arteries on the images using an interactive image analysis tool. The labelling results were used as the ground truth for system’s training and evaluation.

The common performance measurements of sensitivity, specificity and Dice coefficient were used for the evaluation. The larger the measurements, the more similar the result and the ground-truth are. To focus on the segmented coronary artery, the aorta was manually removed from each segmentation result. The method was trained on the six training datasets and tested on the four testing datasets. It obtained a sensitivity of \(0.81 \pm 0.05\), a specificity of \(0.99 \pm 0.005\), and Dice coefficient of \(0.84 \pm 0.03\). One example is shown in Fig. 3. It can be observed that our method performed well on most of the vessels and had limitations with tiny vessels.

Discussion. Schaap et al. [21] proposed a standard methodology to evaluate coronary artery centerline extraction algorithms with a public Rotterdam database. The database consists of two parts. The first part includes 8 CTA datasets and the corresponding reference centerlines. The second part includes 24 CTA datasets. Even though the Rotterdam evaluation framework focuses on the centerlines of four major coronary arteries while our method aims to segment the full coronary artery tree, it is still interesting to evaluate our pre-trained classifier on the public database for data diversity.

Our results on the first part were evaluated under the framework using the provided reference centerlines and software. To tailor our results to be comparable to the reference centerlines, we extracted the segmentation’s skeletons using a thinning algorithm [22]. Before skeletonization, morphological operations of dilation and erosion were employed for hole-filling. The average performance was: 95.2% of overlap (OV),
70.4% of overlap until first error (OF), 98.1% of overlap with the clinically relevant part of the vessel (OT) and 0.41 mm of average inside (AI). The results were encouraging. The AI was about one voxel. It was probably because the hole-filling and skeletonization were conducted on the original images and the minimal magnitude of error was one voxel. Since extra work has been involved to adapt our results for evaluation under the Rotterdam’s framework, the evaluation was viewed as an indirect assessment of our method, thus, was included in the discussion section.

Fig. 3. One example result for illustration (a) segmented left anterior descending artery (top) and right coronary artery (bottom) overlaid with CTA images using curved multi-planar reformation (b) a segmented complete coronary artery tree compared with the ground truth (green: true positives, blue: false positives, yellow: false negatives)

5 Conclusions and Future works

In this paper, we proposed a new representation of coronary arteries. The relative density feature is able to suppress individual variances, and the global feature is helpful in excluding the spurious structures. The composite of features was integrated into the supervised-learning framework to develop a classifier for coronary artery segmentation. The classifier is applicable to diverse images, and has achieved good performance on both our data and public data. Future work will include algorithm improvement on accuracy for the comprehensive evaluation of CHD.

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