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Abstract. Manual analysis of the bulk data generated by computed tomography angiography (CTA) is time consuming, and interpretation of such data requires previous knowledge and expertise of the radiologist. Therefore, an automatic method that can isolate the coronary arteries from a given CTA dataset is required. We present an automatic yet effective segmentation method to delineate the coronary arteries from a three-dimensional CTA data cloud. Instead of a region growing process, which is usually time consuming and prone to leakages, the method is based on the optimal thresholding, which is applied globally on the Hessian-based vesselness measure in a localized way (slice by slice) to track the coronaries carefully to their distal ends. Moreover, to make the process automatic, we detect the aorta using the Hough transform technique. The proposed segmentation method is independent of the starting point to initiate its process and is fast in the sense that coronary arteries are obtained without any preprocessing or postprocessing steps. We used 12 real clinical datasets to show the efficiency and accuracy of the presented method. Experimental results reveal that the proposed method achieves 95% average accuracy.© 2017 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.OE.56.1.013106]

Keywords: computed tomography angiography; optimal thresholding; Hessian-based vesselness; segmentation.

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1 Introduction

With state-of-the-art imaging equipment capable of recording submillimeter details of internal body organs, segmentation algorithms have gained extraordinary notice of the research community in recent years. Recent imaging modalities such as computed tomography angiography (CTA) generate a bulk amount of data that is more than what is actually required. Precise delineation of specific anatomical structure from such complex volumetric data becomes challenging due to the intensity distribution in CTA. Despite intensive research, segmentation of coronary arteries from CTA data remains an active research area due to the complex situation. For detecting abnormalities in vasculatures, a detailed diagnosis demands precisely segmented tubular structures. Therefore, there is a high need for robust segmentation algorithms, i.e., a precise segmentation of coronary arteries to help the clinicians in accurate and fast diagnosis of coronary-related abnormalities.

Deformable contours, level set framework, and Hessian-based analysis are some of the techniques often used for addressing the CTA segmentation problem. However, automatic frameworks are least reported because of complexity issues. Deformable models have been used for effective vascular segmentation by many authors.1–5 Model-based methods simplify the vessel extraction and representation problem by fitting the shape of the vessel to a certain geometric model. These can be fast and intuitive, but the model usually has limited capabilities in representing all possible shapes, such as bifurcations and irregular cross sections, which are often the case for diseased vessels. The construction of such a model remains a difficult task as it is quite difficult to obtain the much required training data that represents all possible variations. According to the literature, level set formulation (geometric active contour model) has been used frequently for delineating anatomical structures from medical images. The ability of level set formulation to handle topological changes makes them an ideal choice for vascular segmentation as the vessel often exhibits complex topology. However, they are slow in computation and require an initial point to grow further, which may cause erroneous segmentation of coronary arteries. Lankton et al.6 utilized a localized active contour approach for detecting the coronary vessels by considering only the voxels representing the heart and ignoring very dark voxels representing air present in the lungs. However, their method requires a single-point initialization within the vessel by a user, which may lead to erroneous segmentation and may increase the processing time. Szymczak et al.7 used a topological approach to track coronary arteries. Their method was capable of locating distal segments. However, validation of the complete coronary vessels was not reported by the authors. In addition, it also required interactive aid from the user for coronary tree identification.

Several algorithms have been reported in the literature for enhancement of vascular structures from images, and the majority of them relies on the second-order Hessian matrix analysis. The seminal work presented by Frangi et al.8 is usually considered the initial vesselness and is, therefore, being used in combination with different methods for segmenting the coronary arteries. Oksuz et al.9 presented a hybrid...
method as a combination of Hessian-based vesselness filter and three-dimensional (3-D) region growing for robust detection and quantification of multiple coronary stenosis with different types and significance from 3-D CT angiography datasets. Khedmati et al.10 presented a similar work for coronary artery segmentation where the authors proposed a seed point adjustment method to avoid wrong path during region growing. However, the methods proposed by Oskuz et al. and Khedmati et al. both have the tendency to suffer from leakages, which requires some external aid from the user to remove unnecessary components to obtain the final segmentation. Jin et al.11 performed the vessel segmentation using an improved level set method followed by morphological top-hat transformation and Hessian-based multiscale filtering for vessel enhancement. In their work, they introduced an external constrained term $F_{\sigma}$ based on sigma used in the Hessian matrix with Gaussian function convolution into the level set to avoid the segmentation leakage of nonvascular structures. However, their method cannot obtain expected results when the image contrast is very low. Wang et al.12 segmented the coronary arteries by evolving the initial surface of the arteries obtained through Hessian-based multiscale filtering with that region-based active contour method to capture the borders of the arterial lumen. However, all these methods require more processing time because of the involvement of multiple steps in segmenting coronaries.

It is notable that very few resources addressing the question of fully automatic coronary segmentation from CTA data exist in the literature. Almost all the existing methods require some extent of user interaction, which makes them prone to user expertise and prior knowledge. Therefore, in this paper, we propose an automatic algorithm that is capable of extracting coronary arteries completely without any aid from the user. The proposed method has exploited the Frangi’s response as its foundation and is based on the averaging scheme to statistically threshold the vesselness. The method does not require any preprocessing step and is free from human intervention; thus, it extracts the coronary arteries quickly and efficiently from a given CTA data cloud.

The rest of this paper is arranged into the following sections. Section 2 explains the proposed methodology along with examples. Experimental results on various datasets are shown in Sec. 3. The conclusion of this study is given in Sec. 4.

2 Proposed Method
The block diagram of the proposed method is shown in Fig. 1. Given a CTA volume, the problem of finding the coronary arteries in the CTA data cloud commences by determining the vesselness measure using Hessian-based analysis. The vessel enhancement filter based on Hessian analysis responds at each voxel by calculating likelihood of such voxel to be vascular structures. For handling different vessel sizes, the enhancement response is calculated at different scales and voxel is assigned the strongest scale likelihood values.

After computation of the Hessian-based vesselness measure, to create a binary representation of coronary arteries, a global optimal thresholding algorithm is applied on the output of the enhancement filter. The binary image is obtained by first finding the local optimal threshold for each slice of a dicom volume. Then, the mean of local optimal thresholds, which acts as a global threshold, is computed and applied on the complete resulting Hessian-based vesselness measure. Then, a fraction of this global threshold is used to segment the Hessian-based vesselness. Furthermore, to make the process automatic, the descending aorta is detected from the given original CTA volume and an intersection is performed between the outcomes of the detected aorta and the segmented Hessian-based vesselness to ensure the accurate segmentation of coronary arteries by discarding any other noncoronary small fragments. Algorithm 1 contains the description of the pseudocode that is used for finding the local optimal and the global threshold. where “$N$” is the total
no. of slices in a CTA volume and “k” is a factor that acts as a tuning parameter for the selection of global threshold.

Major drawback of Hessian-based vesselness is its inherent limitation that makes the computational process passive. It becomes difficult to distinguish line and step edges using the Frangi measure, resulting in increased false positives. Since Hessian-based vesselness suffers from the intensity inhomogeneity problem, a global threshold as a mean intensity may not be sufficient and may result in losing potential distal coronary points, as shown in Fig. 2. Therefore, we propose a method that uses a fraction of optimal mean intensity to extract the coronary arteries efficiently and accurately without losing coronary distal points. The fraction of optimal mean intensity is represented by “k” in the algorithm. There is a trade-off between the value of k and the complete structure of arteries. As shown in Fig. 2, when the value of k is

1. For each slice of CTA volume,
   a. Consider only the four corners of the image as background pixels and the remaining pixels as belonging to the object.
   b. For every step $t$, calculate the mean intensity of background pixels $\mu_{BG}^t$ and the mean intensity of the remaining pixels that constitutes the object $\mu_{OB}^t$.
\[
\mu_{BG}^t = \frac{\sum_{(i,j) \in \text{background}} f(i,j)}{\text{no. of background pixels}} \quad \mu_{OB}^t = \frac{\sum_{(i,j) \in \text{object}} f(i,j)}{\text{no. of object pixels}}.
\]
   c. Then, the updated optimal threshold is computed using the following equation:
\[
T^{(t+1)} = \frac{\mu_{BG}^t + \mu_{OB}^t}{2}.
\]
   d. Update the background and the object pixels of image, using the new threshold value $T^{(t+1)}$.
   e. Return to (b) until the difference between the successive thresholds is minimal.

2. After determination of optimal threshold for each slice, the global threshold $T_{global}$ for the entire volume is computed using the following equation:
\[
T_{global} = \frac{(T_1 + T_2 + \ldots + T_N)}{k \times N}.
\]

![Fig. 2 Results for different values of “k.”](http://opticalengineering.spiedigitallibrary.org/ on 02/28/2017 Terms of Use: http://spiedigitallibrary.org/ss/termsofuse.aspx)
very small, the algorithm is unable to extract the complete arterial tree, whereas the larger value of \( k \) causes the algorithm to extract some noncoronary components as well. This is because the optimal threshold will become very low when dividing by 10 and hence unable to differentiate between coronary and noncoronary objects, as can be seen in Fig. 2(e). After performing extensive experiments, we get optimal results at \( k = 6 \).

To show how thresholds can be effectively chosen, we ran several experiments on large image datasets with a variable number of slices and intensity variations. It is found that for all of the cases our algorithm works effectively for choosing thresholds because we applied thresholding on the vesselness map that consists of only those voxels, which belong to the coronary arteries. Since thresholding is applied on the probability of the vesselness instead of intensity, our algorithm is not affected by intensity variations of datasets. The only limitation of our algorithm is that the time for effective segmentation increases linearly with the number of slices, as can be seen in the graph shown in Fig. 3.

Moreover, to extract the coronary arteries without human intervention, we exploited an automatic aorta detection technique within the proposed method. It is known that aorta is a major vessel that can be used as a landmark to guide segmentation of other structures such as coronary arteries. To track the coronaries automatically, we exploited the anatomical knowledge that coronary arteries initiate from the descending aorta as the two largest objects joining the aorta. In this way, we can also get rid of some remaining small disconnected components that are not the part of coronary arteries. By considering the circular anatomy of aorta, we sequentially detect the circles in starting axial slices by applying the Hough transform technique\(^6\) with radius between 40 and 70. To achieve a robust generalization, for each slice, the top 30 best fitting circles are considered as initial candidates from a series of obtained circles. We selected 30 best fitting circles because different CTA volumes may exhibit irregular variability in the shape of the aorta. We filter out the selected circles by overlapping the current segmented aorta with the one detected in the previous slice and the circle that satisfies 60% overlapping is selected. To further filter out the circles, distance is computed from the center of the circles between the detected circles of the current slice and the previous slice. The circle with the minimum distance is selected as the aorta. After detection of the aorta, the coronary arteries are recognized by extracting the two biggest components connected with the aorta. The process of the aorta detection is shown in Fig. 4.

3 Experimental Results

For testing the proposed method, we segment 12 clinical CTA volumes to isolate the left and right coronary arteries. The size of each volume is 512 × 512 and the number of slices varies from 300 to 350 for each volume. For performance evaluation, we compared our results with that of the ground truth data obtained from the radiologist. Furthermore, we compute the segmentation efficiency using the OM defined in Eq. (1). This measure is defined as the ratio of the intersection of segmented coronary arteries \( S_A \) to the union of the segmented arteries area \( S_A \) and the manually segmented area \( S_G \).

\[
OM = 2 \times \frac{S_A \cap S_G}{S_A + S_G}.
\]  

When the obtained segmentation is well matched to that of the reference ground truth, the OM will get close to 1. The
value of OM approaches to zero in the case when no similarity is found to the reference data. The segmentation results in Fig. 5 show that the proposed method is able to detect the coronary artery components in each slice accurately and without leakages.

To demonstrate the superior performance of the presented method, we further provide a side by side comparison of the obtained segmentations with that of Lankton’s approach and Khedmati’s approach for seven randomly selected CTA datasets; the results are shown in Fig. 6, which consists of four...
columns. The first column of Fig. 6 represents the ground truth data of the coronary arterial tree, which is obtained from the radiologist. The second and third columns from the left represent the results obtained through Lankton’s approach and Khedmati’s approach, respectively, whereas the last column represents the detected coronary arterial tree for seven randomly selected CTA volumes obtained from the proposed method.

It can be seen that the proposed method is able to correctly detect the complete structure of both the left and right coronary arteries along with their branches to the distal ends. However, Lankton’s method often fails to get the complete structure of the coronary arteries because of the leakage of contour during the curve evolution process. The segmentation obtained through Khedmati’s method also suffers from leakages and breakages, as shown by the green box in Fig. 6. On the contrary, the coronary arterial tree acquired by the proposed method is much better than the one obtained from Lankton’s and Khedmati’s approaches, which consist of various leakages and gaps as depicted by the green boxes.

Fig. 6 Comparison of obtained segmentation with Lankton’s and Khedmati’s methods.
in the second and third columns from the left of Fig. 6. It is observed that Khedmati’s method is unable to obtain coronary arteries to their distal ends because their method uses a hard threshold during the preprocessing stage, which may remove some of the distal potential coronary artery components.

Table 1 shows the comprehensive evaluation for all the methods, where the average of the OM obtained for all the datasets is shown. The OM is computed to validate the 2-D segmentation. It can be observed that the proposed method achieves 30% improvement in OM as compared with Lankton’s approach and 45% improvement as compared with Khedmati’s approach. Moreover, to compare the 3-D segmentation shown in Fig. 6, we computed the TPR, the PPV, also known as precision, and the F-measure to measure 3-D segmentation accuracy. TPR, also called sensitivity and recall, measures the portion of positive voxels in the ground truth that are also identified as positive by the segmentation being evaluated. TPR, PPV, and F-measure are computed as follows:

\[
TPR = \frac{TP}{TP + FN} \tag{2}
\]

\[
PPV = \frac{TP}{TP + FP} \tag{3}
\]

\[
F\text{-measure} = \frac{2 \times PPV \times TPR}{PPV + TPR} \tag{4}
\]

As shown by the statistics comparison, the proposed method obtained the best results overall for all the three metrics. As shown in Fig. 6, our method is successful in automatically obtaining the coronary arteries accurately for almost all of the datasets except for a case where CTA volume consists of severe stenosis, as shown by the region enclosed by a green box in Fig. 7. Figure 7 shows four parts: Fig. 7(a) shows the ground truth data and Figs. 7(b) and 7(c) show the segmented arteries obtained by Lankton’s approach and Khedmati’s approach, respectively. The result of the proposed algorithm is shown in Fig. 7(d), where our method has narrowed the lumen, as shown by the area enclosed by the green box. This is because of the presence of severe plaque in the artery. On the contrary, Lankton’s method has completely disconnected the artery from its main branch in the case of severe plaque, as depicted by the green box in Fig. 7(b). Although Khedmati’s method is able to segment the plaque affected region, it is unable to segment the complete coronary arteries to their distal ends.

By looking at the results of Fig. 6, it is observed that the proposed method gives superior performance as compared with Lankton’s method and Khedmati’s method. Lankton’s method requires a single seed point for each artery separately to initiate its active contour evolution, whereas Khedmati’s method requires one or multiple seed points for the region growing process. In contrast to Lankton’s approach and Khedmati’s approach, our method detects the aorta automatically by utilizing the anatomical knowledge of coronary arteries; hence, the proposed method is entirely automatic and does not require any aid from the user. Another drawback of Khedmati’s approach is the use of hard threshold during the preprocessing stage because it may cause the distal coronary artery components to be removed before the segmentation process starts. Even though multiple seed points are required by Khedmati’s approach, their segmentation is prone to leakages and irrelevant components that need to be removed manually after the segmentation is achieved. The segmentation obtained by Lankton’s approach is also prone to leakages due to the slight differences in intensities. In contrast to Lankton’s approach and Khedmati’s approach, the proposed method produces leakage free segmentation whose accuracy does not depend on the manual provision of seed point(s) that often leads to inaccurate segmentation.

### 4 Conclusion

In this study, a method is presented for delineating the coronary arteries automatically from a 3-D CTA volume. The method is based on the averaging scheme that is applied on the Hessian-based vesselness measure and combined with a modified automatic aorta detection technique. The proposed method uses the optimal thresholding in a localized way, which makes it capable of producing a complete coronary arterial tree including the distal ends with correctness and without leakages. The efficiency of the proposed method was illustrated by performing various experiments on real clinical CTA datasets, which show promising results.

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Fig. 7 Extracted coronary arteries for a CTA volume with severe stenosis.
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References

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