ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ISOLATION OF CORONARY ARTERIES BASED ON ACTIVE CONTOUR AND REGION GROWING MODELS WITH AUTOMATED SEED SELECTION

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ABSTRACT

Analysis and examination of huge volumetric data produced by CTA is a tedious and time-consuming task for radiologists when it comes to many patients. Therefore, computer-assisted diagnostic techniques are required to assist the clinical experts for the tracking of coronary arteries in volumetric datasets of heart in an automatic fashion. This paper aims to presents some of the most commonly used segmentation algorithms along with their pros and cons and their solution in the reported literature. This study specifically provides a study of four different techniques that are meant to segment the coronary arteries from volumetric datasets. The efficiency of all these methods has been validated on real clinical CTA datasets. Additionally, statistical comparison of these method is also provided with the help of performance measures including Precision, Recall, Jaccard Index (JI), and F-measure.
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Keywords: *coronary arteries segmentation, active contour, computed tomography angiography, hessian-based vesselness.*

1. INTRODUCTION

Coronary artery diseases are considered as one of the life-threatening diseases. As per the information provided by WHO, heart diseases are the number one cause of deaths leading to mortality rate of 17.9 million every year [1]. A well-timed diagnosis of such diseases is required to have the proper treatment. Now-a-days medical imaging is playing an important role in obtaining the detailed inside pictures of the human body for the diagnosis and investigation procedure. Although, there exist various imaging modalities but Computed tomography angiography (CTA) is well known modality because of its invasive nature and high spatial resolution. CTA provides a bunch of images with a clear view of coronary arteries along with the presence of notable stenosis as shown in fig. 1.

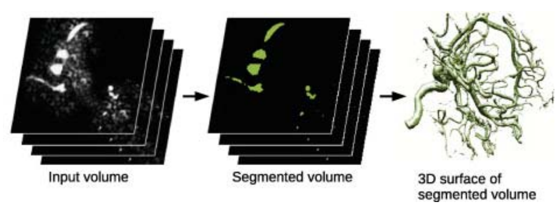

Figure 1. CTA Imaging Of Coronary Arteries And Its Segmentation

However, analysis of such huge data obtained by CTA modality is a tiresome and laborious job. Hence, computer-aided efficient methods are demanded by the clinical experts to ease the task of detecting coronary diseases such as plaque.

Remainder of the paper is structures as follows. Literature review has been described in Section 2. Section 3 discusses the selected methods used for segmentation of coronary arteries.in detail. Section 4 describes the efficiency of the four selected method with the help of experimental results. However, Conclusion and discussion for future work has been presented in Section 5.

2. RELATED WORK

There exist various segmentation methods in the literature that address the problem of isolating the coronary arteries either in automatic or semi-automatic manner. However, due to the varying anatomical information of the human body it is difficult for one segmentation method to produce good results for all types of images. Most of the studies in the literature are based on region growing approach and active contour models. However, both of these approaches require initial point (single or multiple points) to grow further. Hence, the performance of these methods may partly rely on the placement of these starting points [2]. Region growing based approaches [3-5] tend to produce over-segmentation as they often require user intervention for the placement of initial seed [6] and due to the variations in image intensities and noise which may produce holes and hence leads to over-segmented result. Besides region growing methods, another most widely used technique for the segmentation of vessels is based on active contour model which is primarily known as snakes [7]. Active contour acts as an energy minimization function and are utilized by numerous applications to carry out segmentation of the medical images [8 - 9]. To carry out the segmentation, sankes specifies a distinct boundary also known as curvature for the regions of target object [10]. This initially defined boundary starts to deform itself in the presence of various constraints and image forces. The external force pulls it towards the contours of the object and the internal forces that repel the deformation. The active contour keeps on deforming iteratively until the energy associated with the given contour is minimized such that it estimates the true shape of the given object. However, active contour model has one key shortcoming that it will get stuck at a local minimum [1].

From the existing literature, it is evident that level set based [11, 12] approaches are most widely used to carry out the segmentation of medical images specifically. The reason for their frequent use lies in the fact that these methods can deal easily with the topological changes, hence make them ideal selection for vessel segmentation as vessels usually shows complicated topology. However, they may lead to erroneous segmentation of vessels since they require starting point for their evolution and moreover, they are computationally slow. Shawn Lankton and his coworkers [13] have presented an approach to detect the coronary arterial tree from CTA imagery. This approach is based on the localization of the active contour model that only considers the voxels which represents the heart portion whereas the very dark voxels representing the air and lungs are ignored by this model. However, the requirement of the single starting point for the initialization of the segmentation may produce an inaccurate segmentation because of the manual provision of the initial seed. Moreover, it may also increase the overall processing time. Similarly, the topological based approach has been used by Szymczak et al. [14] for the tracking of coronary arterial tree. Although their method produces the segmentation of distal arteries, but the validation of complete coronary arteries has not been reported in their work. Moreover, like Lankon' s approach this method also requires user interaction for the identification of coronary arteries.

Most of the existing segmentation methods enhances the arteries from given images by analyzing the second order Hessian matrix. In this regard, Frangi et al. [15] has presented the seminal work which is generally considered as the initial vesselness. Being initial vesselness, it is combined with different methods to produce a good segmentation of coronary arteries.

Oksuz et al. [16] presented a hybrid method as a combination of Hessian-based vesselness filter and three-dimensional region growing for robust detection and quantification of multiple coronary stenosis with different types and significance from 3D CT angiography datasets. A similar approach was proposed by Khedmati et al. [17]. In their method, the authors proposed a seed point adjustment method to avoid wrong path during region growing. However, these both methods require initial seed point selection, and have the tendency to suffer from leakages. One more similar work based on region growing approach has been presented in the literature by Chuan Zhou et al. [18] where two seed points were required for each of the coronary arteries. However, their method was also relying on the initial seed points provided by the user. Like this another approach has been proposed [5] where region growing approach was combined with Hessian geometrical features to produce the segmentation of different sized vessels.

Zhou et al. [19] presented a method following the steps of heart region extraction, multiscale coronary artery response method for vascular structure enhancement, automated detection of seed points, and 3D dynamic balloon-tracking method for coronary arteries tracking. However, the EM algorithm used in the heart region extraction has low

Journal of Theoretical and Applied Information Technology
15th April 2021. Vol.99. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

efficiency because of the huge amount of points in the CTA volume. Meanwhile, Bouraoui et al. [20] introduced an automated method based on advanced mathematical morphology techniques. They employed a blurry grey-level hit-or-miss transform method to detect seed points automatically. However, the 13 structure candidates employed in their method occasionally fail to detect seed points because they cannot cover all patient conditions.

Zucker [21] gave a brief explanation of various other approaches of region growing. Yin Wang et al. [22] 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.

In this paper, we have compared four different methods [13, 17, 23, 24] for delineating the coronary arteries from challenging CTA Volumes. The reason of selecting these articles is that the method proposed by Lankton [13] is the mostly commonly used active contour-based approach for segmentation purpose. Whereas, the Zai's [24] method targets the limitations of Lankton's approach and provide a solution of those limitations. And, the reason for selection of Khedmati's [17] method lies in the fact that it also requires initial seed point for initiating the segmentation process just like Lankton's approach. The limitation of seed point selection in Khedmati's approach was addressed by Ahsan et. al. [23] where they proposed an automated seed point selection. Hence the above stated facts lead us to select these methods for comparative analysis. The evaluation of all these methods is carried out on real clinical datasets and the qualitative as well as quantitative results are provided.

3. MATERIALS AND METHODS

For segmentation of coronary arteries, several methods exist in the literature but due to the nature of medical images no single method fits to all types of medical images. Most frequently used methods include thresholding, region growing, Hessian-based vesselness, active contour model. This section discusses the details of four different segmentation methods used for delineating the coronary arteries from computed tomography angiography data (CTA).

3.1 Shawn Lankton's Approach

The method presented by Shawn Lankton and his co-workers [13] gives the concept of energy localization. In this method, energy is minimized by incorporating local information with the advantages of region-based methods. Localization of energy gives better performance even for the images contains objects with heterogeneous intensities by following an assumption that interior and exterior regions will be different locally. To understand the concept of localization, this study takes help of mathematical notations. For an image I which is defined on domain Ω, with the representation of a closed curve Γ characterized by zero level set of SDF ϕ such that $\tau = \{x\epsilon\Omega \dashv |\phi(x) = 0\}$ [12, 25]. The interior of the curve $\tau$is identified by approximating the smoothed Heaviside function given by (1).

$$H\phi(x) = \begin{Bmatrix} 1 & \phi(x) < -\varepsilon \\ 0 & |\phi(x)| > \varepsilon \\ \frac{1}{2}\left\{1 + \frac{\phi}{\varepsilon} + \frac{1}{\pi}\sin\left(\frac{\pi\phi(x)}{\varepsilon}\right)\right\} & otherwise \end{Bmatrix} \quad (1)$$

In the same way, the exterior region of curve is described as $(1 - H\phi(x))$. However, the derivative of Heaviside function $H\phi(x)$ is computed to show the area instantaneously neighboring to the curve. Therefore, curve is identified by a smooth form of Dirac delta function as given by (2).

$$H\phi(x) = \begin{Bmatrix} 1 & \phi(x) = 0 \\ 0 & |\phi(x)| < \varepsilon \\ \frac{1}{2\varepsilon}\left\{1 + \cos\left(\frac{\pi\phi(x)}{\varepsilon}\right)\right\} & otherwise \end{Bmatrix} \quad (2)$$

Further, the concept of localization is adapted by introducing a ball function which is defined by (3).

$$B(x,y) = \begin{Bmatrix} 1 & \|x-y\| < r \\ 0 & otherwise \end{Bmatrix} \quad (3)$$

The variables x and y in (3), corresponds to independent spatial variables which indicates a point in the domain Ω, and r defines the radius of the ball. A ball is placed on every point of the curve and its corresponding ball function is computed by incorporating the information of local interior and local exterior regions.

When the point y lies inside the ball, the function is set to 1 otherwise 0. The communication of ball with these regions of a given curve is explained in Fig. 2.

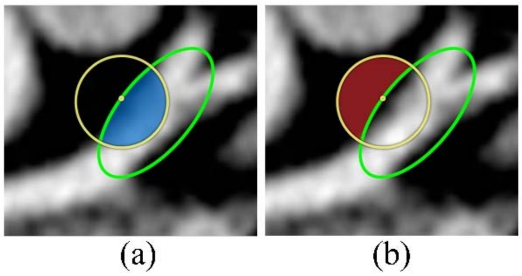

Figure 2. Interaction Of Ball With Contour

Fig. 2 shows an initially drawn curve in green color whereas a yellow dot represents any point x on it. The blue portion as shown in Fig. 2(a) indicates the local interior region of the curve whereas, the red shaded area indicates the local exterior region of the curve as shown in Fig. 2(b).

Hence, (4) defines the final energy function $E(\phi)$ by incorporating the ball information in terms of basic internal energy functional indicated by F.

$$E(\phi) = \int_{\Omega} \delta\phi(x) \int_{\Omega} B(x,y)F(I,\phi,x,y)dydx \quad (4)$$

The function $F(I,\phi,x,y)$ in (4) is a generic form of the internal energy which specifies the local adherence to a given model at each point of the curve. In equation 2.4.1.7, the multiplication with Dirac function, $\int_{\Omega} \delta\phi(x)$ ignores the complexity of image that may rise outside the radius and captures a wider range of object.

For keeping a curve smooth, generally a regularization term is added in almost all snake-based segmentation method. It penalizes the arc length of the contour and weights it by a parameter λ. So, the final energy equation can be defined by (5).

$$E(\phi) = \int_{\Omega} \delta\phi(x) \int_{\Omega} B(x,y).F(I,\phi,x,y)dydx + \lambda \int_{\Omega} \delta\phi(x)\|\nabla\phi(x)\|dx \quad (5)$$

Further, the evolution equation as given in (6) defines the first derivative of energy in terms of ϕ.

$$\frac{\partial\phi}{\partial t}(x) = \delta\phi(x) \int_{\Omega} B(x,y).\nabla_{\phi(y)}F(I,\phi,x,y)dy + \lambda\delta\phi(x)div\left(\frac{\nabla\phi(x)}{|\nabla\phi(x)|}\right)\|\nabla\phi(x)\| \quad (6)$$

3.2 Khedmati's Approach

Khedmati et al. [17] introduced a semi-automatic method for segmenting the coronary arteries from CTA images. His method passes through six stages including pre-processing of CTA data, enhancement of the vessels, extraction of the vessel-centerline, estimation of the arteries cross-section diameter and locating the stenosis. To reduce the processing time, his method rescales the original slices of a CTA volume into smaller size. Khedmati's approach segments the coronaries from a CTA by using a region growing based approach which performs segmentation of region of interest by growing an initially given point into a larger region according to some pre-specified criterion. It searches for the pixels sharing similar properties with respect to some criterion. Firstly, starting point(s) known as seed(s) is (are) provided, and then the method checks for the neighboring pixels to be added into the region one by one if they satisfy certain criterion. However, the primary issues in region growing methods include determination of initial seed point(s) and setting of a similarity measure criterion. These seed points can either be chosen automatically [3-5] or can be provided with manual interaction especially in complicated situations [6]. Khedmati's method adjusts the seed points using the mask adjustment criteria.

The limitation of his approach lies in the initialization of the region through multiple seed manually. Their method produces gapes (spaces) and leakages due to un-fulfilment of the region growing criteria.

3.3 Zai's Approach

The approach presented by Zai et. al [24] is based on the localized active contour model. Their method does not depend upon the manual selection of initial seed points in order to feed to localized energy model. The first phase of this method involves the sequence of operations for locating the correct coronary seed points by employing the shape information of coronary arteries followed by thresholding of Hessian-based vesselness with respect to median and quantile values. Whereas, the second phase makes use of the detected coronary seed points and performs the segmentation of both left and right coronary arteries.

Automatic seed detection framework is adopted because of the reason that manual feeding of initial seed points may fall into wrong paths and may also increase the processing time. The flowchart of seed detection phase is described in Fig. 3.

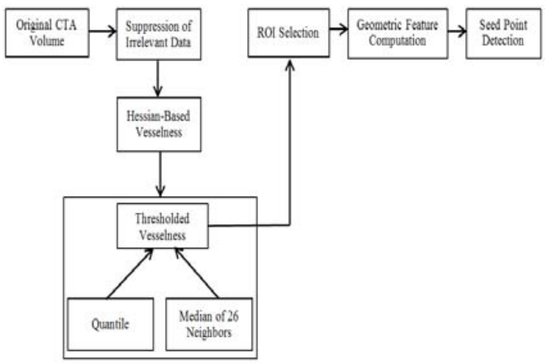

Figure 3. Phase 1: Automatic Seed Detection Process [24]

For the detection of seeds, the shape characteristics of the coronary arteries have been incorporated into thresholded Hessian-based vessel probability map. Thresholding has been performed with respect to quantile and median values to obtain the correct edges of the coronary regions, to get-rid of the irrelevant data and to deal with the step-edge responses that are usually generated because of the intensity inhomogeneity present in medical images. Accurately detected coronary seed points have been used by the subsequent stage of segmentation.

Fig. 4 shows the segmentation phase to detect coronary arterial components in CTA volume. Before the segmentation process starts, an initial mask has been developed on each of the detected coronary seeds that have been further developed during the contour evolution process. The self-adaptation of mask helps in detecting the side branches that may arise away from the aorta.

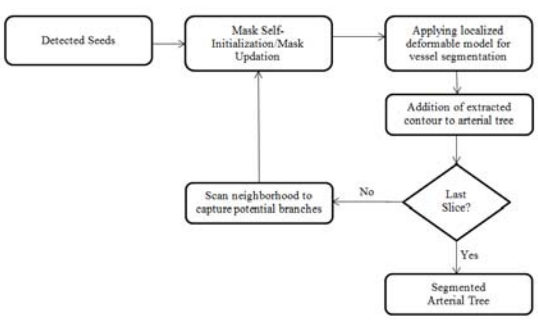

Figure 4. Second Phase: Segmentation Of Coronary Arterial Components [24]

The steps of self-mask adaptation are given below:

1. For each of the segmented component, extract 15*15 neighborhood region around that component.
2. Carry out the following steps on 15*15 region to find all possible coronary candidate,
a. Detect edges using Sobel edge detector.
b. Calculate the length 'L' and curvature 'K' by performing contour tracing and using the following equation

$$K = \sum_{i=1}^{L-1} \left| D[i+1] - D[i] \right|$$

Where, 'L' indicates the total size of the traced contour and 'D' points towards the direction of the movement during pixel tracing. The parameter 'i' is the representation of the current traced pixel.

3. Discard all the non-vascular regions by using the criterion of L > 16 and K<10.
4. Select only those candidates from the left ones whose mean intensity >160.

Evolution of the contour from the initial mask has been started by employing the localized region based deformable model which has been directed to evolve under the guidance of the thresholded Hessian-based vesselness. Having guided by the coarse proposed thresholded vesselness, the contour evolution does not fall into the wrong paths and hence successfully tracks both coronary arteries till their distal ends without leakage of the contour into the neighboring regions. Furthermore, the localized energy model has been directed to deform itself in forward and backward direction from the reference slice used for the seed localization to grab all the potential coronary components that may exist before and after the chosen slice.

3.4 Ahsan's Approach

The method proposed by Ahsan et. al [23] comprises of four sequential steps as shown in fig. 5. Since the raw CTA volume consist of lots of data along with noise. Therefore, first step of their method is to eliminate irreverent data. At this stage, the information is refined by utilizing the fact that coronary arteries are tubular or cylindrical anatomically. Therefore, Hessian based vesselness measure is being used to extract the tubular structures from the given CTA data coarsely which is further refined in the second stage of their methodology. The second phase is of importance as it describes the complete procedure of coarse to fine segmentation of heart arteries by selecting optimal local and global thresholds. An optimal threshold is selected for each of the slice of the given CTA data known as local optimal threshold. The threshold is computed in an iterative fashion until the optimal threshold is obtained when the difference between the successive threshold is minimum.

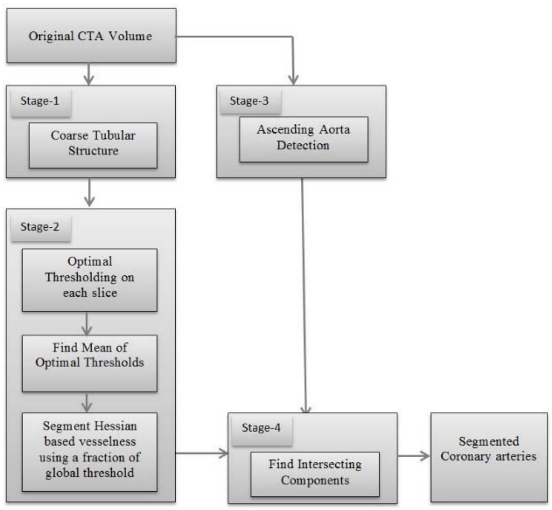

Figure 5. Flow Chart Of Ahsan's Approach [23]

The average of all the local optimal thresholds for each of the slices is used as the global optimal threshold which is further used for the segmentation of the coronary arterial tree. In [23], basically a fraction of global optimal threshold is chosen for an efficient and accurate segmentation, because the use of only average of all local thresholds may not be enough to produce good segmentation results.

The automation of the whole process is achieved in step 3, where ascending aorta is extracted without human intervention using Hough Transform technique and by utilizing the relationship between aorta and the coronary arteries. Finally, in the last step intersection is carried out to detect only the components that correspond to the coronary arteries and to discard the non-coronary arterial components.

4. EXPERIMENTAL RESULTS

To evaluate the performance of all the four methods discussed in Section 2, an intensive experimentation has been carried out on real clinical CTA volumes. Total 13 CTA volumes of patients falling in age group from 42 to 68 years were selected for experiments. Out of thirteen patients five were females and eight datasets belong to male. All the datasets were acquired in the Hanyang University, Seoul Hospital during the period of May 6th, 2015 to May 28th, 2015 by using a same CT scanner. The size of each volumetric image is 512*512 whereas number of slices varies for each dataset in between 288 to 378. An average size of the voxel is 0.37*0.37*0.36 mm^3.

All the experiments are performed using MATLAB on a machine with 2.14 GHz processor and 4 GB RAM. For computing the Hessian based vesselness on multi-scale, the range of scale is set to 2 to 5. The a, β and γ values for controlling the sensitivity of similarity criteria were set to 0.6, 0.5 and 220 respectively. For detecting ascending aorta using Hough transform in Ahsan's method, the value of radius is chosen within the range of 40 to 70 inclusively. To select the reference slice in the Zai's approach for seed detection procedure, the value of constant c_r is used within the range of 0.4 to 0.6. All other parameters for the methods proposed by Zai [24], Lankton [13] and Khedmati [17] have been implemented according to their recommended settings.

However, a big challenge in implementing Lankton's and Khedmati's approaches was the selection of initial seed point(s). As the performance of these methods depends upon the initial seed point(s) despite mask adjustment techniques in these methods. Therefore, to select optimal seeds for these methods on real clinical datasets, we selected seed points(s) as per the recommendations of radiologists.

A visual comparison of all of the four methods proposed by Khedmati [17], Lankton [13], Ahsan [23], and Zai [24] on eight randomly selected real clinical CTA volumes is presented in Fig. 6.

The Zai's method achieves quite better performance by generating the accurate segmentation of the entire coronary arteries (LCA and RCA) without producing the gaps and leakages. In contrast, the segmentation obtained through the Lankton's and Khedmati's method is prone to leakages and gaps, respectively. Besides, these methods are unable to track the entire coronaries till their distal ends and may fail due to the similar intensities of near-by voxels. As opposed to hard threshold used by Khedmati's approach, the selection of a fractional value of the global optimal threshold produce good results for segmentation of coronary arteries.

As can be seen in Fig. 6, Khedmati's method is unable to produce a complete structure of the coronary arteries. Additionally, it results in gaps and leakages as marked by the boxes. This is because of the use of hard threshold in his method which causes the removal of significant coronary components.

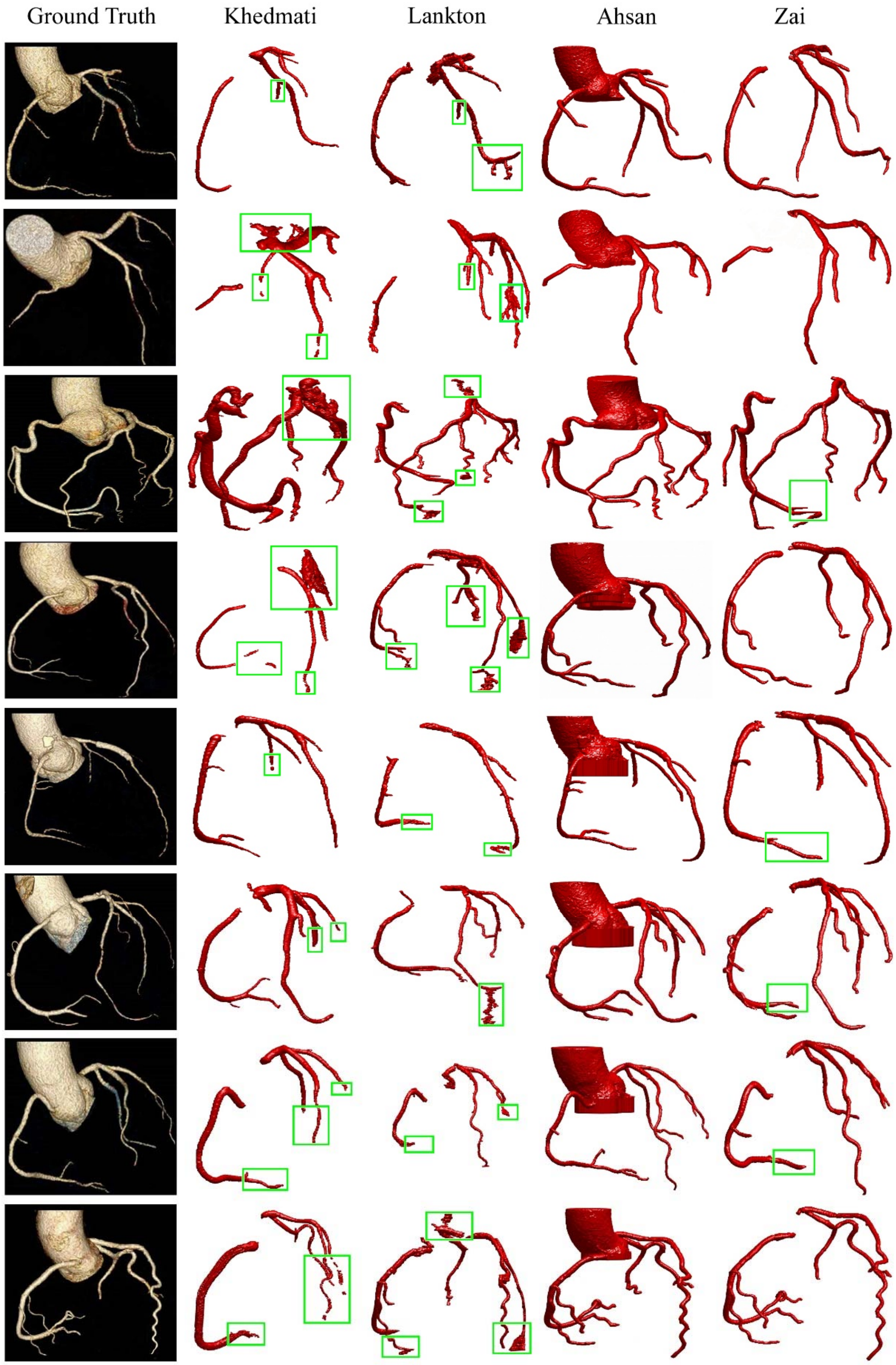

Figure 5. Segmentation Results On Real Clinical Dataset

Journal of Theoretical and Applied Information Technology
15th April 2021. Vol.99. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Although, Lankton's method is capable to produce a complete structure of the coronaries as compared to Khedmati's approach but it suffers from more contour leakage problem especially at the distal ends and hence results in false detections. In Lankton's approach, the contour is evolved with respect to intensity values. However, CTA images exhibits slight intensity variations therefore the contour gets leaked into nearby region where the intensity is not homogeneous locally. In contrast, the Zai's method produces accurate and leakage-free segmentation as shown by the fifth column of Fig. 6.

Moreover, in comparison to the Ahsan's approach, the Zai's method fails to track the arteries to the very distal ends. Especially, in case of right coronary artery, the Zai's method cannot detect the distal ends.

However, in case of the first, second, fourth and last row of Fig. 6, the Zai's method is almost identical to the Ahsan's method. Although, in few cases Ahsan's method produces complete coronary arterial information but as far as execution time is concerned, the Zai's method attains lesser time as compared to the Ahsan's approach. Moreover, the time for Ahsan's method increases linearly as the number of slices increases in a dataset. On the contrary, the execution time of the Zai's method is around 15 minutes.

On average, the time taken by Ahsan's approach is 30 minutes for a data set consisting of 400 to 500 slices which is almost twice of the time taken by the Zai's method. Besides, the time taken by Lankton's and Khedmati's method is lesser than the Zai's and Ahsan's methods, but they are unable to produce accurate and complete information of coronary arteries. The execution time for all four methods is shown in Fig. 7.

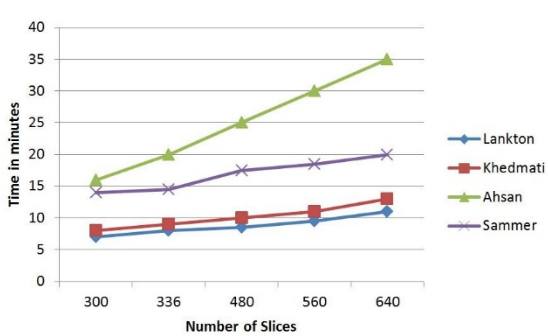

Figure 7. Graph Showing Time Comparison

The statistical comparison of all four methods proposed by Khedmati, Lankton, Ahsan and Zai in terms of TPR, PPV, and F-measure is presented in Table 1

Table 1. Segmentation Comparison On Clinical Dataset (Average)

	TPR	PPV	F-measure
Khedmati	0.41	0.67	0.51
Lankton	0.55	0.78	0.65
Ahsan	0.90	0.89	0.89
Zai	0.86	0.86	0.86

. It can be noticed that Zai's method achieves an improvement of 45%, 31% in terms of TPR when compared with Khedmati's and Lankton's methods, respectively. Whereas, in terms of PPV, Zai's method obtains 19% and 8% improvement in comparison with Khedmati's and Lankton's method, respectively. For F-measure, the Zai's method shows 35% improvement over Khedmati's method and 21% improvement over Lankton's approach. Ahsan's method attains higher values for TPR, PPV, and F-measure but at the cost of time which is almost twice of the Zai's method as depicted by the graph shown in Fig. 7.

5. CONCLUSION

A detailed visual and statistics-based comparison of four different approaches has been provided. Experimentation is carried out on real clinical data sets and the obtained results are validated by the radiologist quantitatively as well as qualitatively. The obtained results of 3D segmentation are validated by the radiologist and it is found that the Ahsan's method outperforms the other discussed method in terms of TPR, PPV, and F-measure. Statistically, the Ahsan's method attains almost 30% improvement as compared to Lankton's method and 45% improvement as compared to Khedmati's method. As far as F-measure is concerned, the Zai's method attains 92% F-measure.

ACKNOWLEDGEMENT

The authors would like to thank Mehran University of Engineering & Technology, Jamshoro, Quaid-E-Awam University of Engineering, Science and Technology, Nawabshah and Liaquat University of Medical and Health Sciences, Jamshoro for

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

providing us the resources necessary to conduct this research.

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