Graph Based Lumen Segmentation in Optical Coherence Tomography Images

Mengdi Xu, Jun Cheng, Damon Wing Kee Wong, and Jiang Liu
Institute for Infocomm Research
A*STAR
Singapore
Email: xumd@i2r.a-star.edu.sg

Akira Taruya and Atsushi Tanaka
Cardiovascular Division
Wakayama Medical University
Wakayama, Japan
Email: a-tanaka@wakayama-med.ac.jp

Abstract—Intravascular optical coherence tomography (IVOCT) is a new invasive imaging system which produces high-resolution images of coronary arteries. Lumen segmentation plays an important role in subsequent analysis of IVOCT images. In this work, we develop a fully automatic lumen segmentation method on IVOCT images. A graph based method is applied to segment the vessel lumen and a match filter based method is employed to detect the guide-wire artifact which caused by guide-wire. A dataset of 500 IVOCT images with manually labeled lumen boundaries is used to evaluate the proposed approach. Overlap dice (OD) is computed to quantitatively evaluate the segmentation result. Results show that the proposed graph based segmentation method is accurate and efficient.

Keywords—OCT; lumen segmentation; graph based method

I. INTRODUCTION

Coronary artery disease, also known as atherosclerotic heart disease, is the most common type of heart disease and cause of heart attacks. Recently, intravascular Optical Coherence Tomography (IVOCT) [1], [2] has emerged as one of the most promising intravascular diagnostic tools with a resolution of 15 um compared with 150 um of intravascular ultrasound system (IVUS), allowing a level of detail never reached before. The IVOCT acquisition has been proved to be effective, safe, and highly reproducible [1].

Lumen properties could be useful in management of coronary artery disease [3]. Many lumen segmentation methods for IVOCT images have been proposed recently [4], [5], [6], [7]. Some approaches are based on thresholding and mathematical morphology [4], [6], [7]. Tung et al. [5] have proposed a geometrically-based method which combines expectation maximization (EM) and graph-cut (GC) algorithms. However, the graph-cut is performed on several overlapping OCT image sequences, which is time consuming. The graph-cut method is also different from our proposed method.

According to lesion characteristics, the IVOCT images could be divided into five groups. They are normal, fibrous plaque (FP), fibroatheroma (FA), plaque rupture (PR), and fibrocalcific plaque (FC). In this work, these five groups of IVOCT images will be denoted as Normal, FP, FA, PR and FC, respectively. The lumen segmentation for these five groups of IVOCT images could be useful for the following image process. However, the existed lumen segmentation method didn’t consider all the groups.

In this work, we propose a novel graph based lumen segmentation approach. The proposed method is fully automatic and works well on all the five groups of IVOCT images. Fig. 1 shows the flowchart of our proposed method. First, the vessel lumen is segmented using graph based method; then the guide-wire artifact region will be detected using match filter based method; finally the two detected regions are combined to get the final segmentation result. Fig. 2 shows some IVOCT images in our dataset.

II. METHODOLOGY

This section introduces two main steps of the proposed method: graph based segmentation algorithm to get the lumen region and guide-wire artifact detection method to find the sector which is caused by guide-wire. Fig. 1 shows the flowchart of the proposed method.

A. Graph Based Lumen Segmentation

The graph based algorithm to segment the lumen is defined as follows. We represent each 2D IVOCT image as a graph of nodes. The pixels (nodes) are connected through edges. A
weight value is assigned to each edge to represent the cost to path through the edge. To travel from one node to another, the total cost will be the sum of all weight values assigned to the edges that connecting the nodes. For our problem, the lumen boundary corresponds to the preferred path. To obtain satisfactory result, it is important to assign appropriate weight values to the edges. Very often, functions of distances between pixels or differences between intensity values are used. After assigned the weight values, graph search algorithm such as Dijkstra’s algorithm [8] can be used to determine the lowest weighted path of a graph between arbitrary endpoints.

Fig. 3 (b) (c) (d) show the segmentation examples. Yellow line shows the catheter, which is removed using Hough transform [9] before segmentation. After that, we transfer the IVOCT image to polar coordinate for further processing (Fig. 3 (c)). The lumen boundary becomes a path which travels across the entire width of the polar image after transformation. Therefore, the graph based segmentation method which introduced in the previous paragraph could be used to segment the lumen.

In our case, the start point is the first pixel of the first column, and the end point is the last pixel of the last column. The weights are calculated based on intensity gradients:

\[ w_{ab} = 2 - (g_a + g_b) + w_{min}, \]  

(1)

Where, \( w_{ab} \) represents the weight of the edge which connects node \( a \) and node \( b \), \( g_a \) and \( g_b \) represent the vertical gradients of the image at node \( a \) and node \( b \), respectively. \( w_{min} \) represents the minimum weight in the graph, which is a small positive number added to keep the system stable.

Since the image has a smooth transition between neighbouring pixels, each node only connecting with its neighbourhoods while other node pairs are disconnected. Therefore for an \( M \times N \) sized image, the adjacency matrix has size \( MN \times MN \) with MNC filled entries. Other entries are set to very high value. Here \( C \) is the number of neighborhood. Chiu et al. [10] applied the graph based method to segment retinal layers. The retinal layers are very smooth, thus only \( 3 \times 3 \) neighborhood is studied. In our work, some rupture cases may have very steep lumen boundaries, therefore we allow a pixel to be connected to another pixel within a \( 3 \times 3 \), \( 5 \times 3 \), or \( 7 \times 3 \) neighborhood. Fig. 3 (a) shows \( 3 \times 3 \), \( 5 \times 3 \), and \( 7 \times 3 \) neighborhood.

After that, we apply Dijkstra’s algorithm [8] to find the lumen boundary, which is lowest weighted path travels through the start point to the end point. The region within the lumen boundary is the segmented lumen. Fig. 3 (d) shows the segmentation result.

B. Guide-wire Artifact Detection

As can be seen from Fig. 3 (d), the detected lumen boundary within the guide-wire artifact region is not smooth due to noise. To resolve this problem, we propose a method to detect the guide-wire artifact.

Given a polar coordinate image after Hough transform, we sum each column to get the intensity curve. Then we convolve the intensity curve with a fixed sized window to get a smoothed curve. The window size is the width of the guide-wire artifact, which is set to be 31 empirically. After that, we estimate the local minimum and global minimum of the smoothed curve. If only one local minimum is found, the location is the guide-wire artifact position. If more than one local minimum is found, we consider two cases: a) if other local minimums are much larger than global minimum, the global minimum shows the guide-wire artifact position; b) if other local minimums have a similar value as global minimum, we apply a match filter to get the guide-wire artifact position.

We transfer the lumen boundary and guide-wire artifact sector back to Cartesian coordinates, detect the joint points of these two boundaries, and connect it using a straight line directly to get the final lumen boundary.

III. Results and Discussions

A. Dataset

We use a dataset with 500 images which covers five groups to evaluate the proposed lumen segmentation algorithm. There are 100 images for each group. The resolution of the IVOCT image is \( 500 \times 500 \). The data were collected by Wakayama Medical University. The images were acquired using optical frequency domain imaging (OFDI) equipment (TERUMO LUNAWave). The equipment produces high quality frequency domain IVOCT images at 158 frames per second.

To evaluate the proposed method, we use the lumen boundary which manually labeled by experts as ground truth. There are two sets of ground truth which labeled by different experts. We will report the result on both ground truth datasets. Fig. 5 (GT1 and GT2) shows the ground truth lumen boundaries which marked by the experts (E1 and E2).
B. Results and Discussions

The accuracy of the segmentation result is estimated using overlap dice (OD):

\[
OD(A, B) = \frac{2|A \cap B|}{|A| + |B|}
\]  

(2)

Where, \(|A|\) and \(|B|\) are number of pixels of the lumen area in image A and B. \(|A \cap B|\) is number of pixels of the overlapping lumen area of image A and B. To better evaluate the proposed method, we compare it with superpixel based method [11].

Table I shows the OD values of the entire dataset. Here superpixel indicates superpixel based method. G1, G2, and G3 indicate graph based method with \(3 \times 3\), \(5 \times 3\), and \(7 \times 3\) neighborhood, respectively. E1 and E2 indicate two ground truths which marked by two experts. The highest OD value for graph based method is 0.9446, while the highest OD value for superpixel based method is 0.9291. It can be seen that, graph based method outperforms superpixel based method significantly. Also, the OD value increases as neighborhood size increases consistently.

Table II shows the OD values for five groups of IVOCT images. It can be seen that graph based method and superpixel based method have comparable performance on Normal group; while for other four groups, graph based method outperforms superpixel based method significantly. One possible reason is that Normal shows the simplest case with clear boundary and less noise, thus easier to get accurate boundary. For both methods, OD values on Normal, FP, FA and FC are much higher than that on PR. That is because most PR lumen boundaries are irregular or not smooth, while other four groups of IVOCT images often have smooth boundaries. When more neighborhoods are considered, the segmented boundary will be more accurate. This result demonstrates that our method has a huge advantage in segmenting lumen boundaries which are not smooth.

Table I

<table>
<thead>
<tr>
<th></th>
<th>Superpixel</th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>0.9254</td>
<td>0.9348</td>
<td>0.9425</td>
<td>0.9431</td>
</tr>
<tr>
<td>E2</td>
<td>0.9291</td>
<td>0.9356</td>
<td>0.9436</td>
<td>0.9446</td>
</tr>
</tbody>
</table>

Table II

<table>
<thead>
<tr>
<th></th>
<th>Superpixel</th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>0.9463</td>
<td>0.9375</td>
<td>0.9456</td>
<td>0.9458</td>
</tr>
<tr>
<td>FP</td>
<td>0.9233</td>
<td>0.9528</td>
<td>0.9607</td>
<td>0.9571</td>
</tr>
<tr>
<td>FA</td>
<td>0.9296</td>
<td>0.9625</td>
<td>0.9647</td>
<td>0.9658</td>
</tr>
<tr>
<td>FC</td>
<td>0.9249</td>
<td>0.9711</td>
<td>0.9759</td>
<td>0.9741</td>
</tr>
<tr>
<td>PR</td>
<td>0.8614</td>
<td>0.8628</td>
<td>0.8833</td>
<td>0.8896</td>
</tr>
<tr>
<td></td>
<td>Superpixel</td>
<td>G1</td>
<td>G2</td>
<td>G3</td>
</tr>
<tr>
<td>Normal</td>
<td>0.9479</td>
<td>0.9356</td>
<td>0.9463</td>
<td>0.9458</td>
</tr>
<tr>
<td>FP</td>
<td>0.9248</td>
<td>0.9537</td>
<td>0.9617</td>
<td>0.9585</td>
</tr>
<tr>
<td>FA</td>
<td>0.9394</td>
<td>0.9627</td>
<td>0.9641</td>
<td>0.9654</td>
</tr>
<tr>
<td>FC</td>
<td>0.9258</td>
<td>0.9547</td>
<td>0.9567</td>
<td>0.9570</td>
</tr>
<tr>
<td>PR</td>
<td>0.8707</td>
<td>0.8682</td>
<td>0.8889</td>
<td>0.8964</td>
</tr>
</tbody>
</table>

Fig. 5 shows some experimental results. Each row shows one input image and the corresponding results. From left to right, the images are: input image, GT1 (ground truth 1), GT2 (ground truth 2), SP (superpixel result) and G (graph result). Here graph result is the result with \(7 \times 3\) neighborhood. We also show the results on the five groups of IVOCT images. (a)(b)(c)(d)(e) are Normal, FP, FA, FC and PR images, respectively. The original images have various lumen boundaries. Fig. 5 (a)(c)(d) show images with clear and smooth boundary; Fig. 5 (e) shows image with non-smooth boundary; and Fig. 5 (b) shows image with blood artifacts. It can be seen that the boundary which detected by graph based method is more...
accurate than that generated by superpixel based method.

IV. Conclusions

In this work, an automated lumen segmentation method which based on graph algorithm is proposed. A match filter based guide-wire artifact detection method is proposed to remove artifacts. The overlap dice (OD) value shows that the proposed system outperforms the superpixel based method significantly. The evaluation images in our method covers five groups of IVOCT images, demonstrating that our method has more potential applications than existing methods.

REFERENCES


