VESSEL SEGMENTATION IN IMAGES OF OPTICAL COHERENCE TOMOGRAPHY USING SHADOW INFORMATION AND THICKENING OF RETINAL NERVE FIBER LAYER

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ABSTRACT

The correct segmentation of blood vessels in optical coherence tomography (OCT) images is an important requirement for better diagnosis of many retinal diseases. Although OCT blood vessel segmentation is often performed by applying vessel detection methods on 2D projection of OCT datasets, some papers investigate the vessel segmentation on OCT slices. The presence of shadows in outer retinal layers is established as the main factor for vessel localization; however, the shadow information fails to localize many important blood vessels. The proposed method is based on anatomical changes of Retinal Nerve Fiber Layer (RNFL) in presence of vessels. In this paper we find the thickening of RNFL by applying a layer segmentation algorithm on OCT slices and combine this information with shadow localization. Furthermore, a vessel detection method based on curvelet transform is also applied on 2D projection of OCTs to be added to localized vessels from OCTs. The results show that combination of vessel detection on 2D projection with vessel localization on OCTs can improve the accuracy up to 0.96 which is promisingly higher than older methods.

Index Terms— Vessel segmentation, OCT image, Retinal Nerve Fiber Layer

1. INTRODUCTION

Optical coherence tomography (OCT) is a powerful imaging modality used to produce information about internal structure of biological tissues [1]. OCT uses the principle of low coherence interferometry to generate two or three dimensional imaging with high cross-sectional resolution of 1-15mm. Since light is 150,000 times faster than sound, in contrast to ultrasound it is not possible to measure the optical echoes directly. Therefore OCT performs based on transporting the information of the investigated specimen and inferring this information with a reference light beam which has traveled a known path length [2]. The underlying technology makes the method a non-invasive imaging modality for observation of the human eye's retinal layers. No other imaging technology is able to present the (layers of the) eye at the same resolution without tissue dissection. Fine retinal vascular networks are also detectable using OCT. However, analysis of fine capillary vessels is difficult, due to noise and ambiguous appearance in the data.

Initial vessel detection filters were proposed in 1998 in [3] and [4]. A vesselness value for each point of the volume is computed by using the eigenvalues and eigenvectors of the Hessian matrix. Another method for detection of centerline was proposed in [5], and an overview of vessel extraction methods is given in [6]. However, all of these methods show unsatisfactory results in noisy data (like OCT) since too many points are misclassified as vessel points while being part of the background.

The eigenvalue decomposition of the Hessian matrix was also used for developing vessel enhancing filters like those proposed in [7] and [8]. An enhancement of cerebral vessels in CT scans by level sets is also proposed in [8]. However, the mentioned method is reported to be efficient for vessel thicknesses 100 and 350 times thicker than the retinal capillary vessels. Many researchers like [9-12] are working on the detection and segmentation of the vascular network in two dimensional fundus images of the eye background and [13] works on 2D projections of OCT images.

In this paper we find the thickening of Retinal Nerve Fiber Layer (RNFL) by applying a layer segmentation algorithm on OCT slices and combining this information with shadow localization. Furthermore, a vessel detection method based on curvelet transform is also applied on 2D projection of OCTs to be added to localized vessels from OCTs.

2. COMBINATION OF TWO METHODS FOR OCT VESSEL SEGMENTATION

Since the retinal bloods absorb the wavelengths of light used in SD-OCT, the volume beneath each vessel becomes less visible and consequently a shadow appears in the position of vessels as an indicator for localizing the corresponding x-axis position. On the other hand, it should be noted that the presence of vessels have also a thickening effect on RNFL, which is a discriminative point in vessel localization [14]. To the best of our knowledge, RNFL thickening hasn't ever been used in automatic segmentation of vessels in other researches. In this paper, we utilize both of the mentioned indicators to localize the position of the vessels in each OCT scan and an overall map of the vessel position can be obtained by putting the obtained locations along together. In order to include both of the indicators in automatic programming, we first apply retinal layer segmentation [15] on each OCT slice. Then, the vertical mean brightness of pixels located between 6th and 12th boundaries of OCT is calculated (the outer retinal layers), in which local minimums indicating the vessel shadows are searched. We also compute the similar value for pixels placed between 2nd and 6th boundaries, presence of a local maximum brightness in which is a sign of RNFL thickening. Since the overall brightness of an OCT scan is not identical in the whole scan (making a drift line), it is not possible to set a constant threshold on each of the mentioned profiles. Therefore, a moving average filter can be first applied on each profile to estimate the drift line to be eliminated, and a constant threshold equal to two-times of the standard deviation is selected for trimming. Figure 1(b, c) present a complete overview of the proposed vessel detection algorithm on OCT slices. In older methods of vessel localization on OCT scans, the total profile of each column was used to identify the shadow positions (Figure 1(a)), instead of reducing the search area to pixels located between retinal layers. Furthermore, a very complicated filtering technique was proposed to find the location of shadows using the total profile [16], which is simply replaced by elimination of drift line and a constant threshold in this proposed method. Furthermore, the vessel localization on OCT scans of such older methods was never employed to produce a vessel map on X-Y coordinates.

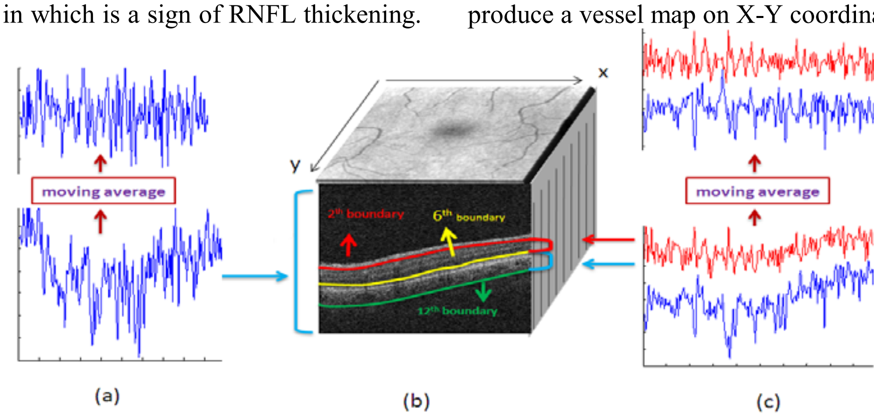

Figure 1. (a) Mean of total profile for each column and applying a moving average to eliminate the drift line, (b) Boundary detection on the selected OCT scan to produce the mean intensity profiles of the layers located between 2nd to 6th boundary, and the ones located between the 6th to 12th boundary, (c) Mean of partial profiles for each column and applying a moving average to eliminate the drift lines.

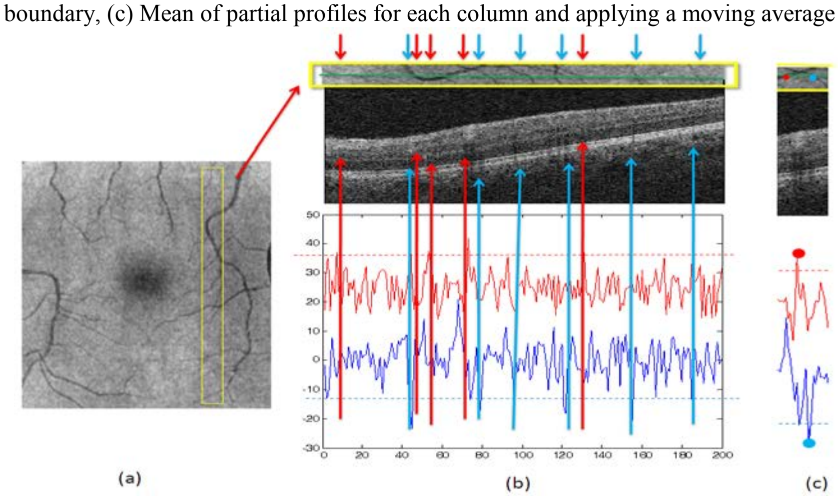

Figure 2. (a) The mean image obtained by taking the mean value of vertical axis pixels (reference image to point out the accuracy of the proposed vessel segmentation algorithm on OCT scans), (b) Correspondence between the shadows, RNFL thickening and blood vessels. The red vertical lines show the correct accordance between the RNFL thickening and some blood vessels. The blue vertical lines show the correct accordance between the shadows and some blood vessels, (c) Detection of vessels using the RNFL thickening search which cannot be localized by finding the shadows (red point is a vessel determined by RNFL thickening which cannot be detected by shadow method).

Figure 2 shows the correspondence between the shadows, RNFL thickening and blood vessels. The red point in Figure 2 (a) shows a vessel determined by RNFL thickening which cannot be detected by shadow method.

It should be mentioned that the most popular method for production of a 2D map of vessels on OCT scans is based on applying traditional methods of fundus vessel segmentation on the mean image obtained by taking the mean value of vertical axis [13] (shown in Figure 2 (a) and 3 (a)). We employed fundus vessel segmentation based on curvelet transform [17] to localize the vessels with acceptable precision. Similar to what we may see in most of similar methods, we should perform a length filtering in final step of the algorithm to remove short and incorrect structure. Furthermore, as proposed by [13], we may take advantage of shadow presence in outer retinal layers and produce the mean image by taking the mean value of pixels in vertical axis located between boundaries 6 to 12 (Figure 3(b)). This map is more reliable in vessel detection since the macular darkness is removed and the vessels have more contrast. Finally, the thick vessels can be localized ideally with this method and we proposed to mix the results of “vessel segmentation on the mean image” with “vessel localization on each OCT scan” to identify the thinner vessels along with the thicker ones obtained from mean image projection.

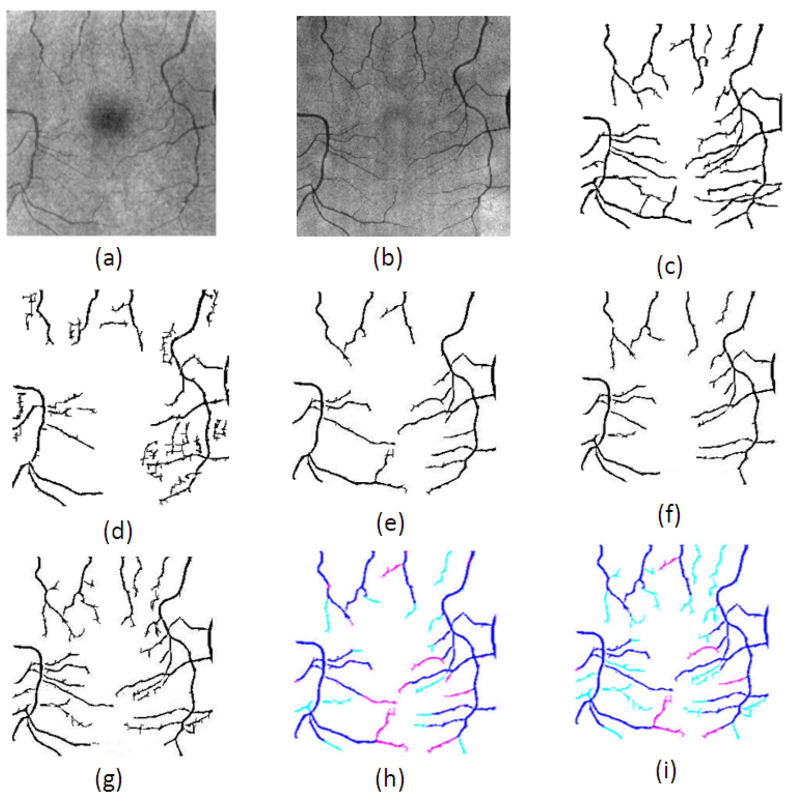

Figure 3. Visual comparison of performance for vessel segmentation of OCT images (in colored figures the blue lines indicate the joint information of two combinatory methods, and two other colors (turquoise and pink) point out the information from each method). (a) The mean image obtained by taking the mean value of vertical axis pixels,(b) The mean image obtained by taking the mean value of vertical axis pixels ones located between the 6th to 12th boundary (reference image to point out the accuracy of the proposed vessel segmentation algorithm on OCT scans), (c) Manual segmentation, (d) Method 3 (Curvelet based vessel segmentation on (a)), (e) Method 4 (Curvelet based vessel segmentation on (b)), (f) Method 1, (g) Method 2, (h) Method 5 (Combination of Method 1 and Method 4), (i) Method 6 (Combination of Method 2 and Method 4).

3. RESULTS

An automatic vessel segmentation system for spectral 3D OCT scans has been presented. The results show that the vessel segmentation works well and that the selected method is proper for vessel detection on OCT images. The above algorithm for vessel segmentation was tested on twenty macula centered spectral 3D OCT scans of 20 normal subjects acquired using a Zeiss Meditec Cirrus OCT scanner. Each volume has $200 \times 200 \times 1024$ voxels corresponding to $6 \times 6 \times 2$ mm^3. The result of segmentation of blood vessel in MATLAB using our algorithm is shown in Figure 3. In order to compare our results with recently proposed methods, we implemented methods demonstrated in Table 1. Visual and numerical comparisons of performance of methods in Table 1 for vessel segmentation are also shown in Table 2 and Figure 3.

Table 1. Description of the proposed methods for comparison.

	The algorithm	Figures
Method1	Find mean of the total profile for each column and apply a moving average to eliminate the drift line. Then find the minimums less than a predefined threshold.	Figure 1(a, b) and Figure 3(f)
Method2	Find mean of partial profiles of the layers located between 2nd to 6th boundary, and the ones located between the 6th to 12th boundary and applying a moving average to eliminate the drift lines. Then find the minimums less than a predefined threshold in pixels located between the 6th to 12th boundary and find the maximums higher than a predefined threshold in pixels located between the 2nd to 6th boundary.	Figure 1(b, c) and Figure 3(g)
Method3	Vessel segmentation on the mean image obtained by taking the mean value of vertical axis	Figure 3(a, d)
Method4	Vessel segmentation on the mean image by taking the mean value of pixels in vertical axis located between boundaries 6 to 12	Figure 3(b, e)
Method5	Combination of Method 1 and Method 4	Figure 3(h)
Method6	Combination of Method 2 and Method 4	Figure 3(i)

Table 2. Comparison of performance measures for vessel segmentation of OCT images

	TPR	FPR	Accuracy
Method 3	0.9512	0.7592	0.9192
Methode4	0.9484	0.9750	0.9496
Methode1	0.9494	0.8738	0.9408
Methode2	0.9575	0.8145	0.9403
Methode5	0.9615	0.8689	0.9549
Methode6	0.9636	0.8118	0.9620

4. RELATION TO PRIOR WORK

To the best of our knowledge, this is the first work for OCT vessel segmentation using the information of RNFL thickening in combination with shadow localization for vessel positioning. The recent work of Lu [16] for OCT layer segmentation included vessel segmentation on OCT slices with only utilizing the shadow information, the priority of this proposed method on which is fully discussed above. Many other methods like [13, 18] were only based on retinal vessel detection on 2D projection of OCT data, which is explored in the previous paragraphs in more detail. Another recent work [19] employed active shape model to segment blood vessel contours in axial direction; but the mentioned paper is mostly focused on localization of vessels on OCRs rather than making a vessel map from retina.

In this work we combine the information from OCT slices with vessel detection of 2D projection to surpass the mentioned older works.

In conclusion, the new method seems to have important advantage over older methods which makes the accuracy of the method higher than other vessel segmentation approaches. The performance of the method is fast and the implementation is relatively simple in comparison to more complicated algorithms.

5. CONCLUSION

The proposed method is based on anatomical changes of Retinal Nerve Fiber Layer (RNFL) in presence of vessels. In this paper we find the thickening of RNFL by applying a layer segmentation algorithm on OCT slices and combine this information with shadow localization. Furthermore, a vessel detection method based on curvelet transform is also applied on 2D projection of OCTs to be added to localized vessels from OCTs.

The results show that combination of vessel detection on 2D projection with vessel localization on OCTs can improve the accuracy up to 0.96 which is promisingly higher than older methods.

In future studies we will show how would the algorithm fare if the curvelet part would be replaced with one of the other existing 2D vessel segmentation algorithms.

6. ACKNOWLEDGMENT

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