A CELLULAR AUTOMATA BASED SEMI-AUTOMATIC ALGORITHM FOR SEGMENTATION OF CHOROIDAL BLOOD VESSELS FROM ULTRAHIGH RESOLUTION OPTICAL COHERENCE IMAGES OF RAT RETINA

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ABSTRACT

Abnormal changes in choroidal blood flow have been linked to various retinal diseases, such as Diabetic Retinopathy (DR) and Age related Macular Degeneration (AMD), which at later stages can lead to blindness. Therefore non-invasive and precise evaluation of choroidal blood flow can aid the diagnosis, treatment and monitoring of retinal disease progression. Doppler Optical Coherence Tomography is an imaging technique capable of measuring blood flow velocity and visualization of retinal and choroidal blood vessles. However accurate assesment of retinal and choroidal blood flow requires precise measurement of the blood vessel thickness. The presence of speckle noise and low image contrast of OCT tomograms makes this task very challenging.

This paper proposes a cellular automata based semi-automatic algorithm for the segmentation of choroidal blood vessels. The proposed approach propagates user-defined points in order to identify the vessel boundaries, allowing a thickness profile to be extracted. The performance of the algorithm was tested on a series of retinal images acquired from living rats with a high speed, ultrahigh resolution OCT system (UHROCT). Experimental results show that the proposed approach provides precise thickness profiles even in the sub-optimal conditions of low image contrast in the UHROCT images.

Index Terms— Cellular automata, semi automatic segmentation, ultra high resolution optical coherence tomography (UHROCT), choroidal blood vessels.

1. INTRODUCTION

Optical coherence tomography (OCT) is an imaging technique that has the ability to acquire non-invasive, high resolution and 3-dimensional images of the structural composition of biological tissue [3, 4]. One of the most advanced biomedical applications of this imaging technique is use for non-contact, 3D imaging of human and animal retina. Morphological features that can be viewed and measured from retinal OCT tomograms — drusen, cysts, macular holes, and retinal / choroidal blood vessels — can be used as markers in retinal disease diagnostics and progression. For example, the retinal nerve fiber layer thickness is an important marker for the clinical diagnosis of glaucoma [5, 6].

Since retinal diseases can affect blood flow in the retinal vessels, precise assessment of flow changes can prove a useful clinical diagnostic. Doppler OCT has been developed in the past 15 years as an expansion of traditional OCT technology, allowing for imaging and measurement of blood flow velocity in retinal vessels. Although Doppler OCT can provide very precise measurement of flow velocity, calculating the total blood flow in a retinal vessel requires knowing the blood vessel thickness or cross-section. Because retinal OCT tomograms are affected by speckle noise, the task of automatic segmentation and sizing of retinal blood vessles is difficult. Speckle noise in OCT images causes difficulty in the precise identification of the boundaries of layers or other structural features in the image either through direct observation or use of segmentation algorithms. Furthermore, the low contrast in some OCT retinal images, related to sub-optimal imaging conditions or from the high haemoglobin absorption of light, can also cause malfunction in the segmentation algorithms or reduce their precision. Even more challenging is the segmentation of choroidal blood vessels due to further reduced image contrast at greater imaging depth.

The field of image segmentation is very mature and many methods [7, 8] are available for biomedical image segmentation. Realizing the fact that unsupervised segmentation methods are not suitable for biomedical image segmentation, several model-based problem-specific and semi-automatic segmentation methods [9, 11] have been proposed for biomedical image segmentation. However, the low signal noise to ratio of OCT imaging along with a small difference in refractive index between blood vessels and water content make the choroid blood vessel boundary indistinct from the foreground. As a result, none of the existing segmentation methods can be directly applied to identify the boundaries of choroid blood

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vessels. As a result, such tasks have been carried out, manually, by trained experts. Such manual segmentation by trained experts is not only time consuming, but also tedious and error prone.

In this paper, a novel semi-automatic algorithm is proposed to precisely measure the thickness of the choroid blood vessel. The proposed approach uses a cellular automata based semi-automated segmentation algorithm to identify the outer boundary of the choroid blood vessel and then the orientation of the boundary of the choroid vessel is identified using an eigen-decomposition. The thickness profile of the choroid vessel is computed with respect to the direction of the largest eigenvalue.

The rest of the paper is organized as follows: A brief description about cellular automata based image segmentation is provided in Section. 2. The proposed approach is described in Section. 3. Finally, the experimental results are demonstrated in Section. 4

2. CELLULAR AUTOMATA BASED SEGMENTATION ALGORITHM

Cellular automata (CA) first prossed by Von-Neuman. [12] is a popular discrete model widely used in computability theory, mathematics, theoretical biology and microstructure modeling. CA is a regular lattice consisting of a set of sites. Each sites can have finite number of states, for example for a two class case, the states of each site can be modeled as "On" or "Off". Recently, researchers have been attempting to formulate image segmentation problem using finite cellular automata theory [10, 11].

The fundamentals of CA based segmentation follows. Consider P and $p \in P$ be set of sites in a discreet lattice $\pounds$. Assume $I = \{I(p)|p \in P\}$, $L_t = \{L_t(p)|p \in P\}$, $\Omega = \{\Omega(p)|p \in P\}$, $S_i = \{S_i(p)|p \in P\}$ be set of random fields on P representing the measured entity (usually an image), label field associated with the measured entity, neighbor hood of the measured entity, and strength of the label field L_t, respectively. The term t represents the iteration number. A CA is usually defined using a triplet $A = [L_t, S_t, \Psi]$ respectively, where Ψ is a similarity measure that controls the likelihood of state transition for $t-1$ to t. The change in state of the level field L from $t-1$ to t are function of $L_{t-1}(p)$, $S_{t-1}(p)$ and $\Psi\left(\Omega\left(p\right), p\right), p \in P$. Therefore, the state or label field of site $p, p \in P$ at t $L_t(p)$ can be expressed as a triplet $\{L_{t-1}\left(p\right), S_{t-1}\left(p\right), \Psi\left(\Omega\left(p\right), p\right)\}$.

This paper have proposed a novel noise robust technique to update the strength of each sites $S_t(p)$, and to define a similarity measure Ψ of CA proposed by Rother et. al. [11].

3. PROPOSED APPROACH

Proposed approach consists of two steps: 1) identifying the boundary of the choroid vessel using a cellular automata based semiautomatic segmentation algorithm and 2) measuring the thickness profile of the choroid vessel by first determining the orientation of the identified boundary.

Algorithm 1 $\underline{v}^c$ = Function CA(I, τ)

1: Initialize the S_0 and L_0 as

$$S_0(p) = \begin{cases} 1 & \text{if } p \text{ is a seed pixel} \\ & \text{or foreground seed} \\ 0 & \text{otherwise} \end{cases},$$

$$L_0(p) = \begin{cases} -1 & \text{if } p \text{ is a user defined background seed} \\ 1 & \text{if } p \text{ is a user defined foreground seed} \\ 0 & \text{otherwise} \end{cases},$$

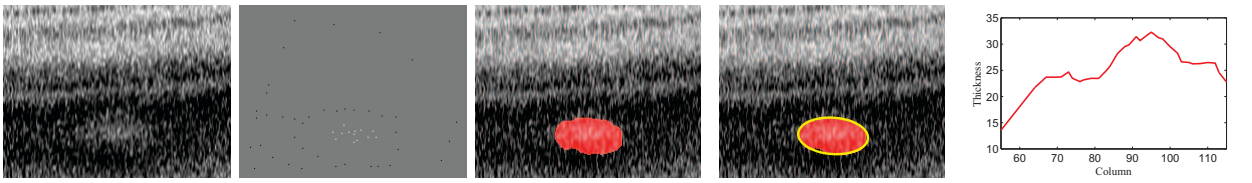
2: $t = 1$; $L_t = \{\}$;
3: **while** $L_t \neq L_{t-1}$ **do**
4: $S_t = S_{t-1}, L_t = L_{t-1},$
5: **for** p = P (all pixels) **do**
6: $\Omega^l = \Omega(p), \Omega^{l^*} = find(\Omega^l \neq 0),$
7: Update $\Psi(\Omega^{l^*}, p)$ using (1
8: $T = max\left(S_t\left(\Omega^{l^*}\right)\psi\left(\Omega^{l^*}, p\right)\right)$
9: **if** abs$(T - S_t\left(p\right)) \leq \tau$ **then**
10: $L_t\left(p\right) = \arg\max\left(S_t\left(\Omega^{l^*}\right)\psi\left(\Omega^{l^*}, p\right)\right),$ $S_t\left(p\right) = T,$
11: **end if**
12: **end for**
13: $t = t + 1.$
14: **end while**

3.1. Cellular Automata choroid Vessel Segmentation

Since, proposed approach is designed as a semi-automatic segmentation technique, a user defines set pixel as background and another set of pixels as foreground (choroid vessel) as shown in Fig.1. Then we employ a cellular automata based propagation technique as described in Algorithm. 1 to label a given retinal image as background and choroid vessel. Proposed cellular automata based segmentation algorithm is a different propagation techniques than the traditional cellular automata based image segmentation techniques. Additionally, proposed approach incorporate noise robust similarity function to precisely identifying the choroid blood vessel. The propagation techniques used in proposed approach is presented in Algorithm. 1. The similarity function used in the proposed approch can be decribed as:

$$\Psi(\Omega^{l^*}, p) = \frac{1}{Z_c}\exp\left(-\left(c_1 f_1 + c_2 f_2 + c_3 f_3\right)\right) \qquad (1)$$

The term c_1, c_2 and c_3 are relative weight factor for f_1, f_2 and f_3, respectively. The user defined constant Z_c is used to



(a) Cropped image (b) Seed pixels (c) Segmented vessel (red) (d) Estimated ellipse (yellow) (e) Thickness of the segmented vessel as a function of column.

Fig. 1. Steps involved in the proposed approach. The seed pixels corresponding to the back-ground and fore-ground are shown in black and white. The segmented choroid blood vessel and the estimated ellipse are shown in third and fourth rows respectively (red and yellow). The thickness of the choroid blood vessel as function of the column is show in fifth column.

make Ψ a probability function. The similarity functions f_1, f_2 and f_3 are used to measure the similarity between pixel p and q and are defined as follows: $f_1 = \|E(I(p)) - E(I(q))\|$, $f_2 = \left\|E\left(I(p)^2\right) - E\left(I(q)^2\right)\right\|$ and $f_3 = \|p - q\|$. f_1, f_2 and f_3 penalize the the first order intensity moment variation, second order intensity moment variation and spatial variation, respectively.

3.2. Choroid Vessel Thickness Profile Measurement

The pixel corresponding to the choroid vessel of a given retinal image is computed from the converged label field L_t. Let X and Y are the locations corresponding to choroid vessel of the retinal image. Let $\Sigma = cov(X, Y)$ be the covariance matrix representing the locations of the choroid vessel. We apply a singular value decomposition method to extract the two eigen vector e_1 and e_2 corresponding to the two eigen values λ_1 and λ_2. As shown in Fig. 1, proposed approach approximate the choroid vessel as an ellipse using these eigen values and eigen vectors. Then the thickness profile of the choroid vessel is computed in a direction perpendicular to the eigen vector corresponding to the major axis of the ellipse.

4. RESULTS

The segmentation and measurement accuracy of the proposed approach is demonstrated on a series of OCT tomograms acquired from the retinas of living rats with a research grade UHROCT system. All animal experiments were conducted in accordance with an ethics protocol approved by the University of Waterloo Animal Ethics Committee. A detailed description of the UHROCT system and more information on the animal experiments can be found in [1, 2]. Briefly, the imaging system provides 3um axial and 5um lateral imaging resolution in the rat retina at an image acquisition rate of 46 frames/s. The system's sensitivity is 100dB for 1.4mW optical power of the imaging beam incident on the rat's cornea, which is in accordance with laser safety regulations outlines in the ANSI standard. Each retinal OCT image is comprised of 1000 A-scans and 512 pixels and allows for clear visualization of all intra retinal layers, as well as the choroidal vasculature (Fig. 2) As shown in Fig. 2, presence of speckle noise blurs the boundary between the choroidal blood vessels and the surrounding tissue, thus limiting the precision of direct assessment of the blood vessels thickness.

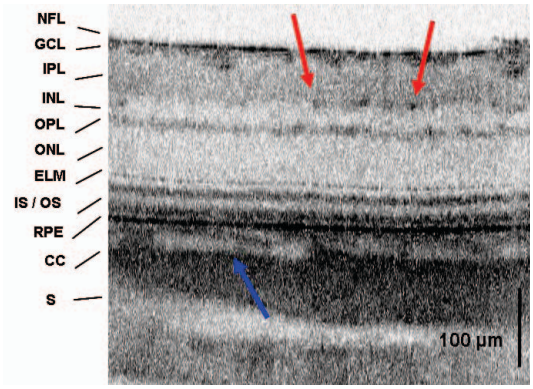
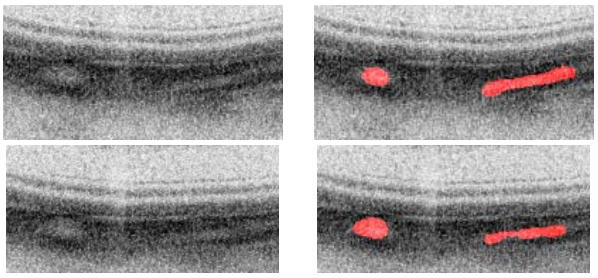


Fig. 2. Two dimensional image of the rat retina acquired in-vivo away (left) from the optic disk. The image was acquired at a rate of 47 A-scans /s with a state of the art UHROCT system operating in the 1060nm wavelength region. The system provides 3um axial and ¡5um lateral resolution in the rat retina with SNR of 100 dB at 1.4mW optical power incident on the rats cornea. Blue arrows point at choroidal blood vessels. Red arrows point at surface blood vessels (retinal arteries and veins).

Fig. 1 shows a small section of a rat retina image near the retinal pigmented epithelium (RPE) that includes a cross-section of a choroidal blood vessel. When the proposed algorithm is applied to the image, automatic segmentation of the blood vessel cross-section is achived. The segmented area (Fig. 1(c)) is fitted with an ellipse (Fig. 1(d)) to allow precise measurement of the vessel's cross-section and size (Fig. 1(e)). Some more segmentation results using proposed approach are demonstrated in Fig. 3.



(a) Cropped images (c) Segmented vessels (red)

Fig. 3. The segmented vessel (red) of two retinal images obtained from the 3D scan of a rat retina.

5. CONCLUSIONS

A semiautomatic segmentation algorithm based on cellular automata theory is proposed to identify the choroid blood vessel of retinal images. The thickness profile of the choroid blood vessel is computed by approximating the the retinal layers using an elliptical model. The performance of proposed method in evaluating the thickness profile of choroid blood vessel is demonstrated using several retinal images.

The preliminary results are very encouraging and the future work includes extending the proposed approach to multiple dimensions and making the propose algorithm fully automatic.

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