Computerized Medical Imaging and Graphics 55 (2017) 42–53

Contents lists available at ScienceDirect

Computerized Medical Imaging and Graphics

journal homepage: www.elsevier.com/locate/compmedimag

Automated layer segmentation of macular OCT images via graph-based SLIC superpixels and manifold ranking approach

Zhijun Gao[a,b], Wei Bu[c,*], Yalin Zheng[d], Xiangqian Wu[a]

[a] School of Computer Science and Technology, Harbin Institute of Technology, Harbin 150001, China
[b] College of Computer and Information Engineering, Heilongjiang University of Science and Technology, Harbin 150022, China
[c] Department of Media Technology and Art, Harbin Institute of Technology, Harbin 150001, China
[d] Department of Eye and Vision Science, Institute of Ageing and Chronic Disease, University of Liverpool, UCD Building, Liverpool L69 3GA, United Kingdom

ARTICLE INFO

Article history:
Received 31 January 2016
Received in revised form 19 June 2016
Accepted 21 July 2016

Keywords:
Optical coherence tomography (OCT)
Segmentation
Graph
SLIC superpixels
Manifold ranking

ABSTRACT

Using the graph-based a simple linear iterative clustering (SLIC) superpixels and manifold ranking technology, a novel automated intra-retinal layer segmentation method is proposed in this paper. Eleven boundaries of ten retinal layers in optical coherence tomography (OCT) images are exactly, fast and reliably quantified. Instead of considering the intensity or gradient features of the single-pixel in most existing segmentation methods, the proposed method focuses on the superpixels and the connected components-based image cues. The image is represented as some weighted graphs with superpixels or connected components as nodes. Each node is ranked with the gradient and spatial distance cues via graph-based Dijkstra's method or manifold ranking. So that it can effectively overcome speckle noise, organic texture and blood vessel artifacts issues. Segmentation is carried out in a three-stage scheme to extract eleven boundaries efficiently. The segmentation algorithm is validated on 2D and 3D OCT images in three databases, and is compared with the manual tracings of two independent observers. It demonstrates promising results in term of the mean unsigned boundaries errors, the mean signed boundaries errors, and layers thickness errors.

1. Introduction

Optical coherence tomography (OCT) is first introduced in 1991 by (Huang et al., 1991), and it is a powerful, noninvasive and high resolution imaging modality used in the diagnosis and assessment of a variety of ocular diseases such as glaucoma and diabetic retinopathy (Wang et al., 2009; van Dijk et al., 2009; Cabrera DeBuc and Somfai, 2010; Zhao et al., 2014). Particularly, with the recent advancement of spectral domain optical coherence tomography (SD-OCT), higher resolution and more data have been acquired for clinical diagnosis (de Boer et al., 2003). But lacking fast and accurate quantification approach for more data, it is inconvenient for ophthalmologists or clinicians to directly diagnose for retinal diseases by calculating total retinal thickness, nerve fiber layer thickness, or outer plexiform layer thickness. Therefore, it becomes increasingly urgent to need an automated retinal layers segmentation approach in OCT images for clinical diagnosis or investigation.

Motivated by this need, the retinal layers segmentation algorithms based on the single pixel's intensity and gradient information have been mainly explored, and focused on the delineation of some intra-retinal layers during the last decade. Initially, the retinal layers segmentation mainly employed an image's peak intensity and gradient methods to segment only a few layers and extract to retinal boundaries, and investigated in (Koozekanani et al., 2001; Ferníandez et al., 2005). Then, active contour models have been built in retinal layers segmentation (Mujat et al., 2005; Mishra et al., 2009). Comparisons of initial methods, contour algorithms appeared good performance in resistance to 2D noise and in error, but has the limitation of selecting pre-determination of the initial seed points that are used in the convergence of the optimal path. Several recent researchers have explored the use of pattern recognition techniques for retinal layers segmentation. Mayer et al. employed a fuzzy C-means clustering technique to segment nerve fiber layer (Mayer et al., 2008). Kajíc et al. (2010) proposed a accurate and robust segmentation method of intraretinal layers with a novel statistical model. Vermeer et al. (2011) also introduced a six retinal layers segmentation method based on support vector machine (SVM) classifiers. With the application of the graph cuts techniques for image segmentation, and graph cuts techniques emerged as one of the important retinal layers segmentation. Combining with spatial constraint information, Garvin et al. used graph cuts to extract nine boundaries (Garvin and Abramoff, 2009). Chiu et al. (2010) employed a dynamic programming techniques to extract eight retinal boundaries. Yang et al., (2010), also

* Corresponding author. Tel.: +86 451 8641 2871; fax: +86 451 8641 3309.
E-mail addresses: zhjgao@163.com (Z. Gao), buwei@hit.edu.cn (W. Bu).

http://dx.doi.org/10.1016/j.compmedimag.2016.07.006
0895-6111/

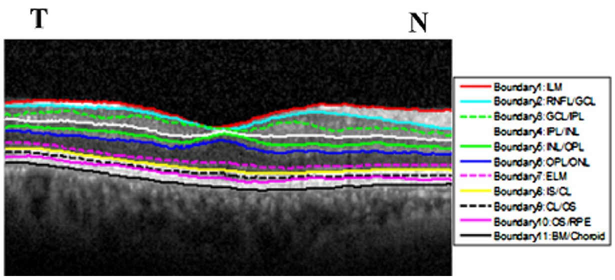

Fig. 1. Illustrates eleven intra-retinal boundaries from top to bottom: boundary 1 ILM, boundary 2 NFL/GCL, boundary 3 GCL / IPL, boundary 4 IPL/INL, boundary 5 INL/OPL, boundary 6 OPL/ONL, boundary 7 ELM, boundary 8 IS/CL, boundary 9 CL/OS, boundary 10 OS/RPE, and boundary 11 BM/Choroid. (N: nasal, T: temporal).

used a dual-scale gradient information model to segment eight retinal layers. The graph search technique based on the single-pixel information can guarantee to find the global optimum, nevertheless it is relatively susceptible to speckle noise or artifact.

Recently, Kafieh et al. (2013, 2015) successfully used a coarse grained diffusion map method to segment eleven retinal layers and to determine the thickness map, the method like super-pixels based approaches can reduce the effects of unavoidable noise in OCT images, however, it needs indirectly detect boundaries by single pixel, and its time-consuming is relatively high in the coarse graining computation. Cha and Han (2014) also presented an intelligent tracking kernel method that could segment nine boundaries of eight retinal layers, but its processing time is also relatively long. Xinjian Chen and Fei Shi et al. successfully proposed a multi-resolution graph search based surface detection method to automatically segment the retinal layers in 3-D OCT data with serous retinal pigment epithelial detachments (Shi et al., 2015).

Most existing retinal layers segmentation algorithms mainly focus on the single pixel or region based on its intensity or gradient within a local context, whereas there is no an algorithm focuses on the whole edge-based image cues to automatically segment the retinal layers. Besides, it is inevitable that some intrinsic speckle noise, organic texture and blood vessel artifacts make difficult to exactly segment retinal layers.

In this work, inspired by superpixels, a novel three-stage using graph-based SLIC superpixels and manifold ranking approach is focused on intra-retinal layer segmentation of OCT images due to its eleven intra-retinal boundaries mainly correspond to high, middle or low contrast in pixels intensity, positive or negative vertical gradient values, and their spatial relationship between intra-retinal boundaries. Fig. 1 illustrates eleven intra-retinal boundaries we desired to find in macular spectral-domain OCT images. It is relative to single-pixel, the proposed approach is based on the superpixels and connected components designated as nodes, so that it is able to well avoid the intrinsic speckle noise, the possible presence of organic texture and blood vessel artifacts. The research demonstrates that such a proposed approach is able to automatically segment eleven boundaries of ten retinal layers in OCT images, and improve the accuracy, efficiency, and robustness of retinal layers segmentation.

In summary, our main contributions are as follows:

(a) Application of the superpixels and connected component, it can well avoid some disturbs from the intrinsic speckle noise and organic texture artifacts, and exactly detect boundary ILM and boundary IS/CL.
(b) Application of the manifold ranking and connected component, it can well overcome discontinuity from the intrinsic speckle noise and blood vessel artifacts, and exactly detect the other nine boundaries.

The rest of this paper is organized as follows, In Section 2 briefly introduces SLIC superpixels, manifold ranking method and the construction of the weighted graph, and describes the proposed intra-retinal layers segmentation algorithm via graph-based SLIC superpixels and manifold ranking technology in detail. The experiments and results are presented in Section 3. Finally, Section 4 concludes the paper.

2. Material and methods

2.1. SLIC superpixels and manifold ranking

Based on k-means clustering, Achanta et al. (2012) successfully proposed a simple linear iterative clustering (SLIC) method for generating superpixels, which has been shown to outperform existing superpixel methods in image boundaries, memory efficiency, speed, and their impact on segmentation performance. And the proposed method has achieved great success on image segmentation (Trulls et al., 2014).

Zhou et al. (2004) successfully proposed a manifold ranking method, which exploits the intrinsic manifold structure of data for labeled graph. Essentially, manifold ranking can be viewed as an one-class classification problem (Scholkopf et al., 2001), that is, only positive examples or negative examples are required. Given a dataset $X = \{x_1, x_2, \cdots, x_n\} \in \mathbb{R}^{m*n}$, $x_i \in R^m$, and $i = 1,2,\ldots,n$, some data points are labeled queries that are assigned a positive ranking score (such as 1), and zero to the remaining points. Let a ranking function $f : X \to R^n$, namely, a weighted network is form on the dataset, then, all points repeatedly spread their ranking score to their nearby neighbors via the weighted network, finally, all points except queries are ranked according to their final ranking scores when a global stable state is achieved. In order to conveniently compute the optimal ranking of queries, a graph $G = (V, E)$ is defined for the dataset, where the nodes V are the dataset X and the edges E are weighted by an affinity matrix $W = [w_{ij}]_{n \times n}$, thereby, the degree matrix D is equal to $diag\{d_{11}, d_{22}, \ldots, d_{nn}\}$, where $d_{ii} = \sum_j w_{ij}$. Then, similar to the PageRank and spectral clustering algorithms (Brin and Page, 1998; Ng et al., 2002), the optimal ranking of queries can be obtained by solving the following optimization problem:

$$f^* = \underset{f}{argmin} \frac{1}{2} \left(\sum_{i,j=1}^{n} w_{ij} \left\| \frac{f_i}{\sqrt{d_{ii}}} - \frac{f_j}{\sqrt{d_{jj}}} \right\|^2 + \mu \sum_{i=1}^{n} \left\| f_i - y_i \right\| \right), \quad (1)$$

where the first and the second term are respectively the smoothness constraint and the fitting constraint whose balance can be controlled by the parameter μ the f_i and f_j respectively denote the ranking scores of the data points x_i and x_j, the y_i denotes the ranking score of the query point x_i. Namely, for a good ranking function, the first term should not change too much between nearby points and the second term should not differ too much from the initial query assignment. Certainly, the optimal solution could be conveniently computed by setting the derivative of the above function to be zero, and the optimal resulted ranking function can be written as Eq. (2) by using the unnormalized Laplacian matrix. The Eq. (2) has achieved great success on image saliency detection (Yang et al., 2013).

$$f^* = (D - \theta W)^{-1} y, \quad (2)$$

2.2. Weighted graph construction

A weighted graph $G = (V,E,W)$ is constructed to represent OCT image, and exploit the gradient information and the spatial relationship, where V denotes a set of nodes, E denotes a set of undirected edges and W is defined to the affinity matrix that represents the weights of the edges between two arbitrary nodes. In this