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Learned local similarity prior embedding active contour model for choroidal neovascularization segmentation in optical coherence tomography images

Xiaoming XI[1,2], Xianjing MENG[1], Lu YANG[1], Xiushan NIE[1], Zhilou YU[2], Chunyun ZHANG[1], Haoyu CHEN[3], Yilong YIN[4*] & Xinjian CHEN[3,5*]

[1] *School of Computer Science and Technology, Shandong University of Finance and Economics, Jinan* 250014*, China;*
[2] *Technology Center, Inspur Group Co., Ltd., Jinan* 250101*, China;*
[3] *Joint Shantou International Eye Center, Shantou University and The Chinese University of Hong Kong, Shantou* 515063*, China;*
[4] *School of Computer Science and Technology, Shandong University, Jinan* 250101*, China;*
[5] *School of Electronic and Information Engineering, Soochow University, Suzhou* 215006*, China*

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Dear editor,
Choroidal neovascularization (CNV) is characterized by the growth of new blood vessels in the choroid layer. These new blood vessels break beneath the retina and damage the surrounding retinal tissue, resulting in distorted central vision. As a useful tool for CNV evaluation, optical coherence tomography (OCT) has been widely used in recent years [1]. Medical image segmentation is important in diagnosing diseases [2, 3]. Automatic segmentation of CNV in OCT images can improve the effectiveness of CNV quantification, which plays an important role in the diagnosis of CNV disease.

To the best of our knowledge, no CNV segmentation method has been proposed for OCT images. The active contour model has been widely used for medical image segmentation, and has achieved impressive performance. Chan and Vese [4] proposed the classical piecewise constant (PC) models (also known as Chan-Vese (CV) models, which can segment the objects with weak edges in some situations. They assumed that the intensity distribution of both segmented object regions and background regions must be as uniform as possible. However, this assumption does not often hold true. In order to address the intensity inhomogeneity in magnetic resonance (MR), Li et al. [5] developed a robust level set method by introducing the local intensity clustering property and bias field estimation. To improve the efficiency, Li et al. [6] developed an active contour model based on multiplicative intrinsic component optimization (MICO) for joint bias field estimation and segmentation of MR images. They optimized the bias field using efficient matrix computations. Furthermore, the energy function was convex in each variable, which made the energy minimization more robust. However, Refs. [5, 6] achieved accurate segmentation result for MR images where the intensity inhomogeneity is slowly varying.

OCT images have more complicated intensity distribution. In OCT images, CNV is a compli-

* Corresponding author (email: ylyin@sdu.edu.cn, xjchen@suda.edu.cn)

cated object with irregular shape and size. Moreover, the intensity distribution is uneven within the CNV region. Based on the observation of OCT images, we can infer that the complicated intensity distribution may result in large intensity variation between neighboring pixels within the same tissues, which causes the existing active contour models to fail in achieving satisfactory segmentation performance.

To address this problem, we proposed a learned local similarity prior embedding active contour model (ACM-LSP) for CNV segmentation in OCT images. The proposed segmentation framework consists of the following steps. (1) A local similarity prior learning model based on sparse representation based classification (SRC) and a posterior probability model is proposed to calculate the local similarity prior map. In the generated prior map, the neighboring pixels have similar probability to CNV or background, which is robust to large intensity variation within the same tissue. (2) To incorporate the local similarity prior with active contour model, a new local similarity fitting energy is developed. The local similarity fitting energy can enforce the neighboring pixels to have similar segmentation result and avoid the segmentation error caused by large intensity variation between neighboring pixels. The experimental results on 15 OCT data with CNV demonstrate that the proposed method outperformed the traditional methods.

Local similarity prior learning. We developed a local similarity prior learning model based on SRC and posterior probability model. CNV was first detected coarsely using superpixel and SRC [7]. In this stage, the image was first segmented into superpixels using the simple linear iterative clustering method, and the intensity, texture, and local features [8] were extracted for each superpixel. Then, the superpixels were classified into two classes using SRC. The classification result was used as the CNV detection result. After that, a Gaussian probability model was developed to obtain the local similarity prior map by considering the local property of Gaussian function

$$P(l|x) = \begin{cases} \dfrac{1}{\sigma\sqrt{2\pi}} \mathrm{e}^{-\frac{(\mathrm{cord}(x)-\mathrm{cord}(c))^2}{2\sigma^2}}, & x \in \Omega_{\mathrm{C}}, \\ 0, & x \in \Omega_{\mathrm{B}}, \end{cases} \tag{1}$$

where $P(l|x)$ denotes the probability that pixel x belongs to CNV, and l is the label of pixel x. c denotes the centroid of the detected CNV. $\mathrm{cord}(x)$ denotes the spatial coordinate of pixel x in the image. σ denotes the approximate radius of the CNV, which can be obtained by calculating the mean distances between the centroid and boundary points of the detected CNV. Ω_{C} and Ω_{B} denote the detected CNV regions and background, respectively.

Global intensity fitting energy. Considering the reasonable mathematical properties of MICO [7], we obtain the global intensity fitting energy through its introduction

$$E_g = \int_{\Omega} \sum_{i=1}^{2} |I(x) - w^{\mathrm{T}}(x)B(x)c_i|^2 m_i^q \mathrm{d}x, \tag{2}$$

where $I(x)$ denotes the observed image. $B(x)$ is a column vector whose elements are basis functions $(b_1(x), b_2(x), \ldots, b_M(x))$. Li et al. [6] used 20 polynomials of the first three degrees as basis function similar to the setting used in this study. w denotes the optimal coefficients $w = [w_1, w_2, \ldots, w_M]$ for estimation of the bias field [7]. Moreover, we assumed that the intensity value of pixels within the i-th tissue is constant c_i in the true image, and the fuzzy membership function $m_i(x)$ was introduced to represent the probability that pixel x belongs to the i-th tissue [7]. In this study, we divided the OCT image into two types of tissues, namely, CNV and background. We set $q = 2$ for convenient computation.

Local similarity fitting energy. To avoid the erroneous segmentation caused by large intensity difference between neighboring pixels, a new local similarity fitting energy was introduced to enforce the local coherence of the object/background labels. The local similarity fitting energy is shown as follows:

$$E_{\mathrm{ls}} = \int_{\Omega} \sum_{i=1}^{2} |m_i(x) - p(l_i|x)|^2 \mathrm{d}x, \tag{3}$$

where $p(l_i|x)$ is the learned local similarity prior map. In the obtained map, neighboring pixels within the same tissue have similar probability to CNV or background.

By minimizing the energy function E_{ls}, the local similarity prior can be embedded into the fuzzy membership functions which can indicate the segmentation result. Therefore, the neighboring pixels have similar memberships within the same tissues, which can be used to avoid erroneous segmentation caused by large intensity variation in the local tissues.

Local similarity embedding active contour model. To enforce global intensity coherence and local coherence, the segmentation problem is formulated as the optimization of the sum of global intensity fitting energy and local similarity fitting energy, as shown in (4). α denotes the parameter that controls the tradeoff between global intensity coherence and local coherence. The segmentation result can be obtained by minimizing the energy function $E_{\rm lse}$.

$$E_{\rm lse}(w,c,m) = E_g(w,c,m) + \alpha E_{\rm ls}(m). \tag{4}$$

Similar optimization method [7] was used to obtain the solution for variables w, c, and m. The energy minimization can be achieved by alternately minimizing $E_{\rm lse}(w,c,m)$ with respect to each variable given the other two fixed variables [7]. The segmentation result is obtained according to the membership function m. The optimization details can be found in [7].

Experiments. The experiments were performed on 15 OCT data with CNV, which were acquired using Topcon 3D-OCT-1000 (Topcon Corporation, Tokyo, Japan). Each SD-OCT volume contains $512 \times 1024 \times 128$ voxels. This study was approved by the institutional review board of the Joint Shantou International Eye Center, and adhered to the tenets of the declaration of Helsinki. Accuracy (ACC), dice similarity coefficient (DSC), true positive volume fraction (TPVF), and false positive volume fraction (FPVF) were used as performance indices. ACM-LSP was compared with state-of-the-art segmentation methods, such as threshold based method, graph cut based method (GC), and convolutional neural networks (CNN).

Figure 1 shows the DSC of different methods. ACM-LSP outperformed the traditional methods on DSC, it increased about six percentage points compared with CNN. Other experimental results are shown in Appendix A.

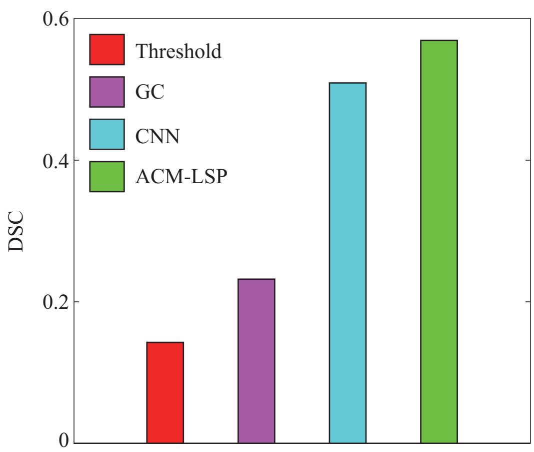

Figure 1 (Color online) Segmentation results of different methods.

Conclusion. We proposed a learned ACM-LSP for CNV segmentation in OCT images. The local similarity prior was first learned jointly using SRC and the developed posterior probability model. Then, the learned local similarity prior was embedded into the active contour model by introducing a new local similarity fitting energy. The developed fitting energy can preserve the local coherence of the object, which can avoid the erroneous segmentation caused by large intensity variation between neighboring pixels. However, the proposed algorithm is 2D, which ignores the relationship between neighboring slices of 3D-OCT data. Therefore, our future work will focus on developing new energy function that extends our method to 3D framework.

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Supporting information Appendix A. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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