Superpixel Classification Based Optic Disc Segmentation

Jun Cheng¹, Jiang Liu¹, Yanwu Xu¹, Fengshou Yin¹, Damon Wing Kee Wong¹, Ngan-Meng Tan¹, Ching-Yu Cheng²,³, Yih Chung Tham², and Tien Yin Wong²,³

¹ Institute for Infocomm Research, Agency for Science, Technology and Research, Singapore
{jcheng,jliu,yaxu,fyin,wkwong,nmtan}@i2r.a-star.edu.sg
² Singapore Eye Research Institute, Singapore
ching-yu_cheng@nuhs.edu.sg, tham.yih.chung@seri.com.sg
³ Department of Ophthalmology, National University of Singapore, Singapore
tien_yin_wong@nuhs.edu.sg

Abstract. Optic disc segmentation in retinal fundus images is important in computer aided diagnosis. In this paper, an optic disc segmentation method based on superpixel classification is proposed. In the classification, histograms from contrast enhanced image channels and center surround statistics from center surround difference maps are proposed as features to determine each superpixel as disc or non-disc. In the training step, bootstrapping is adopted to handle the unbalanced cluster issue due to the presence of peripapillary atrophy. A self-assessment reliability score is computed to evaluate the quality of the automated optic disc segmentation. The proposed method has been tested on a database of 650 images with optic disc boundaries marked by trained professionals manually. The experimental results show a mean overlapping error of 9.5%, better than previous methods. The results also show an increase in overlapping error as the reliability score is reduced, which justifies the effectiveness of the self-assessment. The method can be used in computer aided diagnosis systems and the self-assessment can be used as an indicator of results with large errors and thus enhance the clinical deployment of the automatic segmentation.

1 Introduction

The optic disc (OD) is the location where ganglion cell axons exit the eye to form the optic nerve. Localization and segmentation of OD are very important in the computer aided diagnosis of diseases such as glaucoma. The localization focuses on finding an OD pixel, very often the center. It has been extensively studied for applications in diabetic screening [1]. The main task of the localization is to find the location of OD so that it would not be confounded by large exudative lesions. The process of segmentation is to find the OD boundary. In this paper, we focus on the segmentation problem for applications in automatic glaucoma diagnosis from 2D retinal fundus images. To understand the importance of OD
Fig. 1. Major structures of the optic disc: The region enclosed by the blue ellipse is the optic disc; the central bright zone enclosed by the red ellipse is the optic cup; and the region between the red and blue ellipses is the neuroretinal rim.

Segmentation in glaucoma diagnosis, it is necessary to know the structure of the OD. In 2D retinal fundus image, the OD can be divided into two distinct zones, namely, a central bright zone called the optic cup (OC) and a peripheral region called the neuroretinal rim. Fig. 1 shows the major structures of the OD. In glaucoma diagnosis, the cup to disc ratio (CDR) is used as an important factor [2]. A higher CDR indicates a higher risk of glaucoma. CDR is computed as the ratio of the vertical cup diameter (VCD) to vertical disc diameter (VDD). Very often, the OD is segmented to get VDD and the OC is segmented from the OD to compute VCD. [3]. Thus, it is important to have an accurate OD segmentation. OD segmentation is a challenging task due to blood vessel occlusions, pathology around disc, imaging conditions, etc.

Some approaches have been proposed for OD segmentation, which can be generally classified as template based methods [4], deformable model based methods [6], and pixel classification based methods [8]. In [4], circular Hough transform is used to model the OD boundary because of its computational efficiency. However, clinical studies have shown that the OD has a slightly oval shape with vertical diameter being about 7%-10% larger than horizontal one [9]. Circular fitting might lead to an under-estimated OD and an over-estimated CDR. Thus, ellipse fitting is often adopted [5]. The first two types of methods are based on edge characteristics. The performance of these methods very much depend on the differentiation of edges from the OD and other structures especially the PPA. Examples of PPA are shown as the area between the blue and green lines in Fig. 2. PPA region is often confused to be part of the OD because of two reasons: 1) it looks similar to the OD; 2) its crescent shape makes it form another ellipse (often stronger) together with the OD. Deformable models are sensitive to poor initialization. Very often, the deformation cannot exclude PPA region from the segmented OD if it has been included in the initialization. For example, the red line in the first example in Fig. 2 is the boundary detected by the deformable model based method in [7]. To overcome the problem, a template based approach with PPA elimination was proposed in [5]. By using a PPA detection module based on texture, the method reduces the chance of mistaking PPA as part of the OD. However, it does not work well when the PPA area is small or when the texture is not significantly predominant such as the second example in Fig. 2. Muramatsu et al. [11] compared the pixel