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Robust multi-scale superpixel classification for optic cup localization

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ABSTRACT

This paper presents an optimal model integration framework to robustly localize the optic cup in fundus images for glaucoma detection. This work is based on the existing superpixel classification approach and makes two major contributions. First, it addresses the issues of classification performance variations due to repeated random selection of training samples, and offers a better localization solution. Second, multiple superpixel resolutions are integrated and unified for better cup boundary adherence. Compared to the state-of-the-art intra-image learning approach, we demonstrate improvements in optic cup localization accuracy with full cup-to-disc ratio range, while incurring only minor increase in computing cost.

1. Introduction

As the global leading cause of irreversible blindness, glaucoma is estimated to visually impair 80 million people by 2020 [1]. It is the most prevalent of eye diseases in the United States and around the world. There are approximately 2.2 million diagnosed cases of glaucoma in the United States [2] and 60 million worldwide; however, this figure is significantly underreported due to the slow, asymptomatic progression of the disease, resulting in low disease detection until vision lost sets in. Undiagnosed rates are reported to be nearly 50% in United States and Australia [2] and as high as 90% in Singapore [3,4]. Glaucoma, which is a group of ocular disease, causes permanent damage to the optic nerve. Vision loss due to glaucoma usually begins from the peripheral vision and progress inwards, resulting in a "tunnel vision". This "sneaky thief of sight" is a silent disease as most people do not develop onset symptoms, and do notice the lost of their peripheral vision. When glaucoma patients are referred to the ophthalmologists, severe irreversible visual impairment has often already occurred.

Although vision loss due to this disease is permanent and cannot be restored, studies have shown that early detection and proactive medical intervention are effective in preserving vision and slowing, or even halting, the progression of the disease [5]. A recent economic study has found that technology-based assessment would be a cost-effective option in improving glaucoma detection for eye examination [6].

One of the methods to detect glaucoma is to study the structural damage in the optic nerve head in retinal fundus photographs. In order to gauge the health of the optic nerve in a fundus image, the optic nerve has to be inspected and delineated to identify the optic disc, optic cup and neuroretinal rim [7]. Vertical elongation of the optic cup is a characteristic feature of glaucomatous optic neuropathy [8]. Assessment of the optic cup and optic disc provides important information for glaucoma evaluation, such as the cup-to-disc ratio (CDR). Clinically, these are manually annotated by a trained ophthalmologist.

Several automated methods have been proposed to reduce the labor intensive manual workload. Computerized segmentation techniques for optic disc includes Hough transform [9], template matching [10,11], pixel feature classification [12], vessel geometry [13], deformable models [14] and level sets [15].

In this paper, we address the challenging problem of optic cup detection. Broadly, existing approaches for optic cup segmentation can be categorized into image processing-based strategies and machine learning models. Examples of techniques employing image processing approaches includes thresholding based on the image's intensity [16], active contour [17], level sets [18], active shape models [19]. To further improve on the segmentation, domain priors such as vessel kinks [20], and r-bends [21] have been incorporated. Recently, [22] proposed using graph cuts to segment the optic cup in fundus images, using location and shape priors obtained from OCT.

In recent years, machine learning based approaches have become popular in this domain due to its better accuracy. The use

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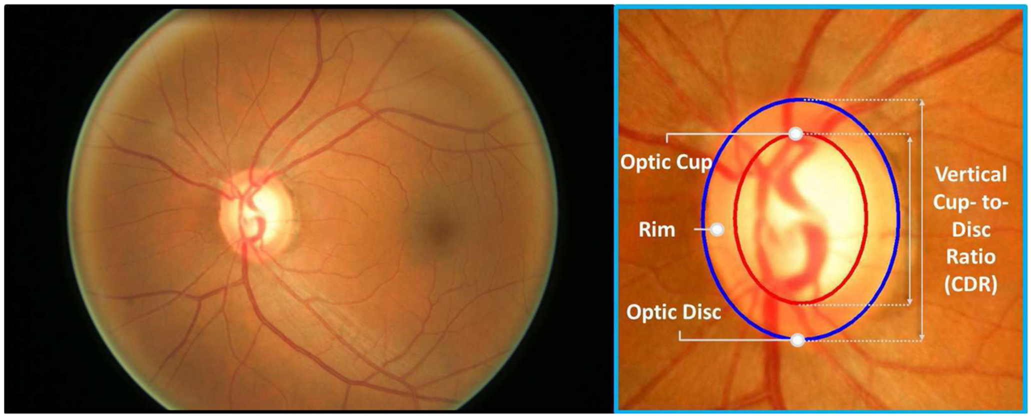

Fig. 1. *Left:* Retinal fundus photograph from the *ORIGA* [33] dataset. *Right:* A close up view of the human optic nerve head, and its structures. Ground-truth of the optic disc and cup are overlaid.

of machine learning methods can be subcategorized into pixel-based, sliding windows and superpixel classification approaches. In [12], the authors proposed using color opponency gaussian filter banks and stereo features on a k-nearest neighbour classifier for pixel-level feature classification. Xu et al. [23] presented a machine learning framework based using a regression model for optic cup segmentation. However, the method is reported to take a long time as it seeks to identify the optic cup as a whole, using a bundle of sliding windows of varying sizes for feature extraction and a RBF support vector regression model to rank each candidate region.

Recently, the use of superpixels for feature classification has been widely adopted in retinal imaging for diseases like pathological myopia [24], age-related macula degeneration (AMD) [25] and glaucoma [26]. Examples of such image over-segmentation methods to acquire superpixels includes graph-based segmentation [27], SLIC superpixels[28], and TurboPixel [29,30]. In particular, for optic cup detection, the supervised superpixel-based classification [26,31] has shown to achieve state-of-the-art performance against other existing approaches [18,21,19]. In [31], a centre surround statistics (CSS) feature descriptor based on biological inspired features were used as features for a non-linear support vector machine (SVM) to perform the task of optic cup segmentation. In [26], besides using the general supervised superpixel classification method, domain prior based on intra-image learning, where each model is learnt from samples from each test image without pre-labeling, is introduced to overcome the illumination differences between training and testing images. A refinement scheme is then used to include structural priors and local context for the final cup detection to further boost its performance. However, the approach assumes a CDR ranging between 0.2 and 0.9, which leads to low accuracy in small and large cup localization. Furthermore, at larger superpixel scales, this will lead to fewer training samples, thus, affecting the overall performance. Using an unsupervised approach, [32] proposed using domain priors, derived from cup pallor and optic cup origin, together with features extracted from superpixels. A label refinement using k-means clustering is then used to achieve the task of optic cup localization. Nonetheless, the accuracy of the supervised approaches [26,31] outperforms the unsupervised method, using fewer assumptions (*i.e.* domain priors).

In this work, we identify two limitations in the existing superpixel-based framework. First, an alternative strategy to reduce the effects of varying illumination between images is proposed and experimentally validated. Next, a general multi-scale superpixel classification strategy is proposed to improve the accuracy and robustness for optic cup localization. We build upon the existing single scale superpixel classification framework in [26,32], and incorporated two novel contributions. First, a multiple model selection and integration scheme using sparse learning is proposed to provide stability in performance variations, arising from repeated random samples selection of training data. Second, multiple superpixel resolutions are integrated for better optic cup boundary adherence and localization. We believe this general framework is also adaptable to other similar classification-based ocular disease CAD applications (Fig. 1).

2. Optimal model selection for multi-scale superpixel classification

Similar to the setup of the work in [26], we start with a disc image to localize the optic cup. First, blood vessels are extracted and the input disc image is enhanced by a contrast normalization scheme. Next, the contrast enhanced image is then segmented into superpixels and blood vessels which overlap with the superpixels are removed. Features are then extracted across multiple superpixel scales, and multiple classification models are trained for each respective scale. To obtain an unique label for each pixel with higher accuracy, optimal superpixel classification models are selected and integrated using a sparse learning approach. The final optic cup area is then identified by using an ellipse to enclose all the pixels predicted as 'cup'. The framework of our overall approach is illustrated in Fig. 2.

2.1. Pre-processing

To reduce the effects on rim/cup misclassification, we used a multi-scale difference-of-closing vessel extraction algorithm by [34] for blood vessel removal. The benefits of this method lies in its flexibility in quick parameter tuning to extract only thicker blood vessels, and the vessel extraction process is simple and fast, requiring only basic morphological operations. A disk structuring element of radius of 16 pixels and 3 pixels for the dilation and erosion operations respectively. As the images are processed at superpixels scale, a blood vessel mask is generated based on superpixels that overlap the vessel extraction mask by at least 75%.

The influence of illumination variances between training and learning images can affect the performance of the trained machine learning models. To reduce these effects, a pre-processing using histogram stretching is performed. For each *RGB* channel in a disc image, the image intensities are represented as a histogram and stretched into [0, 255] to expand the dynamic range and achieve consistency across all the images. This pre-processing histogram normalization accomplishes two goals, 1) it provides better