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Computationally efficient optic nerve head detection in retinal fundus images

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ABSTRACT

This paper presents a computationally efficient method for detection of optic nerve head in both color and fluorescein angiography retinal fundus images. It involves Radon transformation of multi-overlapping windows within an optimization framework in order to achieve computational efficiency as well as high detection rates in the presence of various structural, color, and intensity variations in such images. Three databases of STARE, DRIVE, and a local database have been examined. It is shown that this method provides high detection rates while achieving faster processing speeds than the existing methods that have reported comparable detection rates. For example, the detection rate for the STARE database which is the most widely used database is found to be 96.3% with a processing time of about 3 s per image.

1. Introduction

Computer Assisted Diagnosis (CAD) of retinopathy is currently being used to lower the workload of ophthalmologists as it provides a non-labor intensive approach to the detection of anatomical landmarks and lesions in retinal fundus images. Improvements in the computational efficiency of this CAD system would allow the screening of more patients in a day while using existing camera systems.

The localization of retinal landmarks, in particular optic nerve head (ONH), plays a key role toward identifying pathological conditions; for example in Diabetic Retinopathy (DR) [1,2]. ONH appears as a yellowish region in a color retinal fundus image (see Fig. 1a). The main characteristic of ONH is its rapid intensity variations due to dark blood vessels that are in its vicinity [3]. ONH has three characteristics that have been used in the literature for its localization: (1) it appears as a bright disk nearly 1600 μm in diameter; (2) arteries leave from and veins enter it; and (3) blood vessels diverge from it. As noted in [4], detection of ONH is challenging due to the discontinuity of its boundary caused by large vessels as well as its considerable color or intensity variations as a result of structures such as exudates.

2. Previous works

There exist a large number of algorithms that determine the location (generally center) of ONH or its boundary. Sinthanayothin et al. [3] used the area with the highest average intensity variation to detect ONH using an adaptive local contrast enhancement method. Walter and Klein [5] obtained the ONH center by detecting the center of the brightest connected object in a fundus image. Foracchia et al. [6] used the convergence of vessels to detect the ONH center. Youssif et al. [7] utilized the directional pattern of the retinal blood vessels for the detection of ONH. Their method involved normalizing luminosity and contrast using illumination equalization and adaptive histogram equalization methods. Lu and Lim [8] located ONH based on its bright appearance in a color fundus image by using a set of concentric lines with different directions and evaluated the image variation along multiple directions. The detection of ONH was achieved via the orientation of the line segment having the maximum or minimum variation.

A number of segmentation-based methods have also appeared in the literature. Li and Chutatape [9–11] used an active shape model to detect ONH. An active contour model was also discussed in [12,13] by Osareh et al. to detect ONH. Lowell et al. [14] designed an ONH template and correlated it to the intensity component of the fundus image using the Pearson-R correlation. Another model-based approach was presented by Xu et al. [15], where clustering-based classification of contour points was integrated into an active contour formulation. Wong et al. [16] used the

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1746-8094/

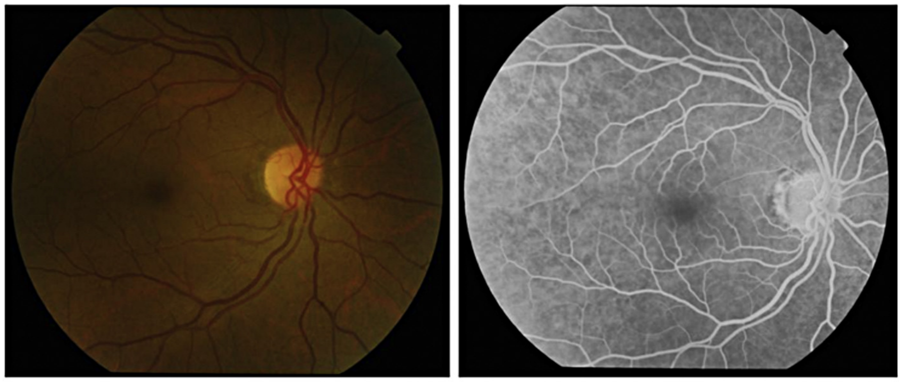

Fig. 1. Retinal fundus images: (a) color fundus image (b) fluorescein angiography fundus image. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

level-set technique followed by ellipse matching. They obtained the ONH location by means of histogram analysis and a modified version of the conventional level-set method using the red channel. Lu [17] designed a circular transformation to capture simultaneously both the circular shape of ONH and the image variation across the ONH boundary. A Hausdorff-based template matching approach together with a pyramidal decomposition were proposed by Lalonde et al. [18]. Haar [19] used illumination equalization in the green channel to address the difficulty of pyramidal decomposition in dealing with large areas of bright pixels toward ONH detection.

Some ONH localization techniques, e.g. [20–24], not only use the ONH characteristics, but also exploit the location and orientation of vessels. For example, Niemeijer et al. [24] presented the use of local vessel geometry and image intensity features. Tobin et al. [25] applied a method that mainly relied on vessels related to the ONH characteristics where a Bayesian classifier was used to classify each pixel in red-free images. Abràmoff and Niemeijer [26] utilized the same ONH characteristics to detect ONH via kNN regression. The method introduced by Abràmoff et al. [27] involved a pixel classification approach. In a recent study, Hsiao et al. [28] localized ONH by an illumination correction operation followed by contour segmentation via a supervised gradient vector flow snake. Yu et al. [29] identified ONH candidates by first using template matching and then by using vessel characteristics. Finally, some methods, e.g. [6,7,19,30], have made use of the fact that major retinal vessels converge into ONH. In [31], we discussed the detection of ONH in fluorescein angiography (FA) retinal fundus images.

The issue of computational complexity of the existing methods has not yet been addressed in a systematic way. In this paper, our aim has thus been to examine the computational complexity aspect. Among the above methods, we have identified the three most computationally efficient methods that have reported relatively high detection rates. These methods are listed them in Table 1. The detection rates listed correspond to the images appearing in the STARE [32] database. As noted in [6,7,32], the detected location of ONH is considered correct or clinically acceptable if its center falls within 60 pixels of a manually identified ONH center.

In this paper, our method initially introduced in [31] is enhanced and extended to color retinal fundus images. Most importantly, the computational efficiency aspect of our method is compared to the ones listed in Table 1 in terms of both computational complexity and detection rate. Furthermore, we have examined three databases instead of only one database. These databases include the two public domain databases of DRIVE [33] and STARE and the private domain database of MUMS-DB used in [31]. In the next section, the details of our computationally efficient detection method are provided.

Table 1
Existing algorithms with relatively high detection rates and relatively low computational complexity.

Methods	Detection rates (%)	Computation time	Machine
Youssif et al. [7]	98.8	3.5 min	2 MHz Intel Centrino 1.7
Foracchia et al. [6]	97.5	2 min (+5 min)[a]	2 MHz Intel Pentium IV *Sun SPARCstation 20
Mahfouz and Fahmy [30]	92.6	0.46 s	2.66 Intel Core2Due

[a] This algorithm needs 5 min to extract the vessel map plus 2 min to detect ONH using the vessel map.

3. Computationally efficient ONH detection method

Our detection method is based on the fact that ONH appears as a bright region in a fundus image. More specifically, Radon transform (RT) is used for this purpose. RT generates the integration of pixel intensities along different directions which leads to making ONH a prominent structure in the Radon space. It is worth pointing out that although it is possible to use other ONH characteristics such as merging points of blood vessels, we have only considered the brightness information here to gain high processing speeds. For example, as noted in the second entry of Table 2, the computational time dramatically increases by using the blood vessel information. In our computationally efficient method, a fundus image is first partitioned into overlapping blocks or sub-images. RT is applied to each block or sub-image. The sub-images exhibiting peaks in the Radon space are then processed in order to locate the ONH. The processing pipeline of our method is illustrated in Fig. 2. The pipeline for fluorescein angiography images slightly differs from the pipeline for color images in terms of the color channel component used. The components of our detection algorithm as well as the computational complexity aspect are further explained in the subsections that follow.

Table 2
Threshold value versus number of ONH candidates.

Threshold	0.94	0.92	0.90	0.88
No. of ONH candidates	8	11	15	18