Optic Disk Detection using Topographical Features

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OPTIC DISK DETECTION USING TOPOGRAPHICAL FEATURES

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Abstract. *We present a new method for optic disk (OD) detection in a retinal image. It is an hybrid approach which uses properties of both appearance and model-based approaches which are mostly used for OD detection. An extrema pyramidal decomposition is employed and hill type topographical features are extracted at the lowest level of the image pyramid. The detected hill points are characterised as candidate OD locations. Later, a confidence measure is derived for each candidate using vessel structure information and candidate with the highest value is declared as final OD location. This method has been tested on different retinal image dataset and quantitative results are presented.*

1 Introduction

Retinal imaging is a common clinical procedure used to record a viewing of the retina. This image may be used for diagnosis, treatment evaluation, and the keeping of patient history. In a retinal image, optic disk (OD) appears as a roughly round region which is brighter than its surround (shown in fig 1 (a)). The location of any abnormality in a retinal image relative to OD is useful for later analysis and classification of pathologies. The detection of OD position is also a pre-requisite for the computation of some important diagnostic indexes for hypertensive retinopathy based on vasculature such as central retinal artery equivalent (CRAE) and central retinal vein equivalent (CRVE) [1]. Thus, OD detection is an important problem in automated retinal image analysis.

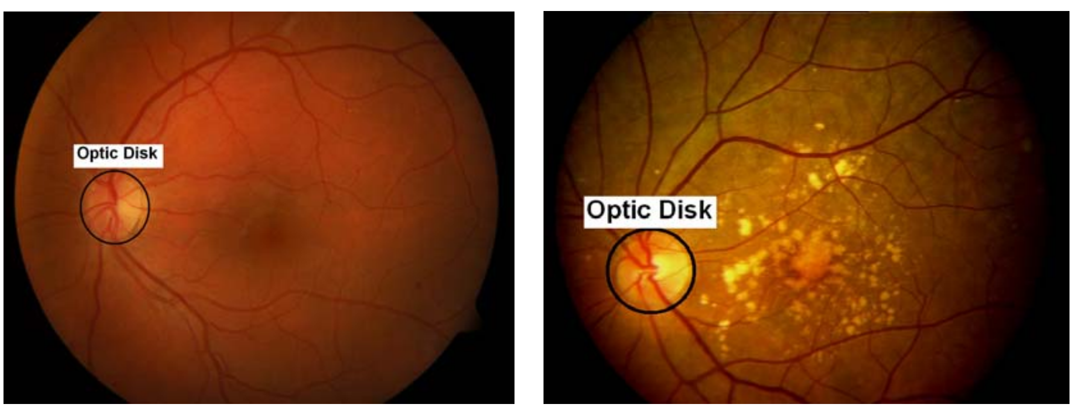


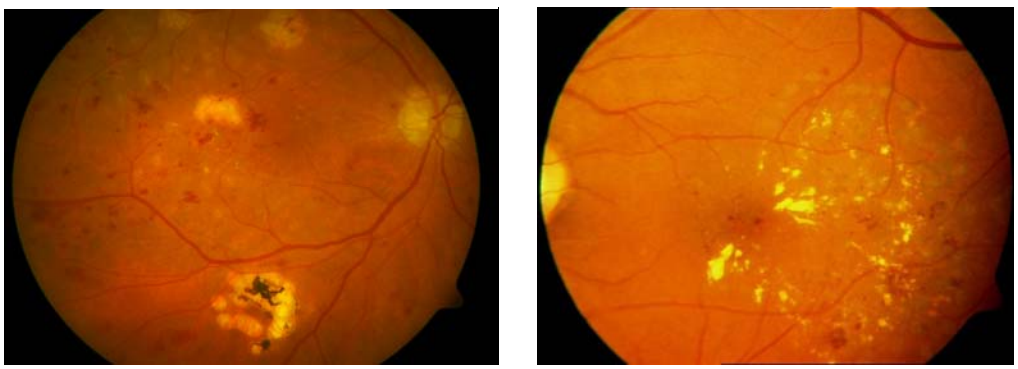
Figure 1. (a) A sample image of a healthy retina, (b) pathological retina

Fig. 1(a) shows an example retinal image where the OD appears as a bright circular area, roughly one-sixth the width of the image in diameter. A distinguishing feature of the OD is that it is region of convergence for the blood vessel network. In a healthy retina, all these properties (shape, color, size, convergence) are useful in identifying OD. However, these properties are subject to a large variance in the presence of retinal lesions which share similar brightness characteristics to OD. Examples of these are shown in fig. 1 (b) and fig 2 (a).

In general, existing OD detection methods can be classified in two main categories: (a)

Appearance-based which exploit features derived from intensity and (b) Model-based which exploit the geometric relationship that exists between the vasculature and the position of the OD in the retina. The appearance-based techniques are based on specific round shape and relatively high brightness of OD, as compared to the rest of the fundus image. Kaupp [2] used split-and-merge segmentation, followed by feature based classification. The features used for classification include intensity and shape of the region. A similar approach was taken in [3], in which the segmentation was accomplished using matched spatial filters of bright and dark blobs. In [4], the OD was detected using the transform of gradient edges into a Hough space describing circle.

The model-based techniques are mainly based on the information provided by the vessel structure, i.e., the fact that all retinal vessels originate from the OD [5]. Niemeijer et al. [6] used a model of the geometrical directional pattern of the retinal vascular system, and implicitly embedded the information on the OD position as the point of convergence of all vessels. A more comprehensive summary of existing OD detection methods can be found in [7].



(a) (b)

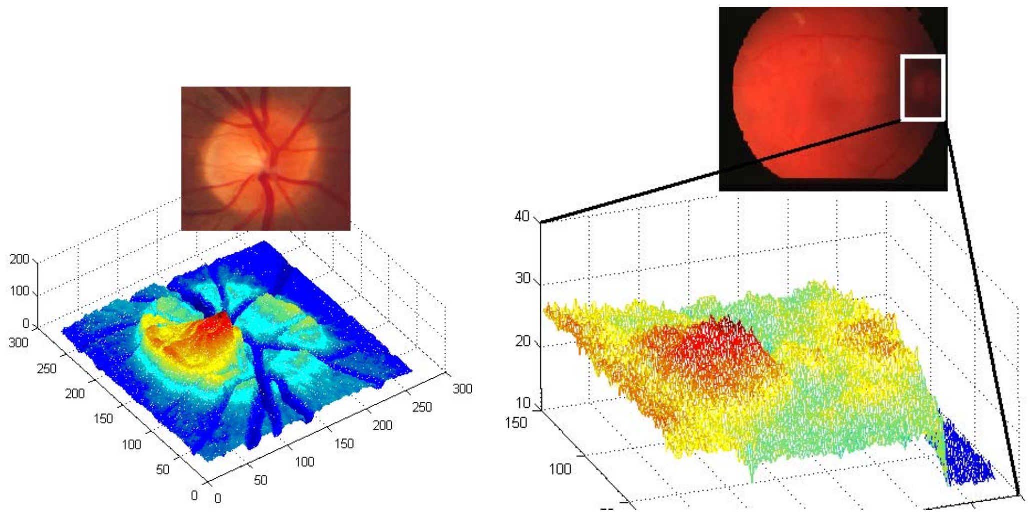
Figure 2. Difficult cases for (a) appearance-based method, (b) model-based method where the vessel network is not visible.

The appearance-based methods fail in pathological retinal images where the pathologies have similar properties to OD as in Fig 1(b) and 2 (a). This is largely overcome by model-based methods which rely on higher order information. However, their detection performance is highly dependent on the presence of main arcades (branches of the vessel tree) in the image which is frequently absent in images taken during large-scale screening programs. For instance, when imaging is carried out at a higher resolution, majority of the vessel network is not visible as shown in fig 2(b). Thus, a hybrid method can potentially ensure reliable and higher detection performance in all possible scenarios.

In this work, we examine the potential of topographical features in the detection of OD. Topographical features have been used to extract structures in various medical images including intensity-defined structures such as vasculature [8]. Here, we propose a novel OD detection technique by deriving candidate OD locations using topographical features and assigning a confidence measure to each candidate, derived using domain knowledge. This method has been evaluated on different datasets [9] [10] [11]. In the next section, we present a scheme for obtaining the OD candidates using topographical information of a given colour retinal image.

2 Curvature-based OD candidate selection

When an image is viewed as a surface, OD appears as a hill shaped structure as can be seen in figure 3(a) and (b). It can therefore be characterised by a curvature (magnitude) maximum in all directions. However, since this corresponds to a local maximum, the scale at which the image is analysed has to be controlled to minimise the number of OD candidates. Accordingly, we use a pyramidal decomposition technique.



(a) **(b)**

Figure 3: (a) and (b) Topographical profiles of OD

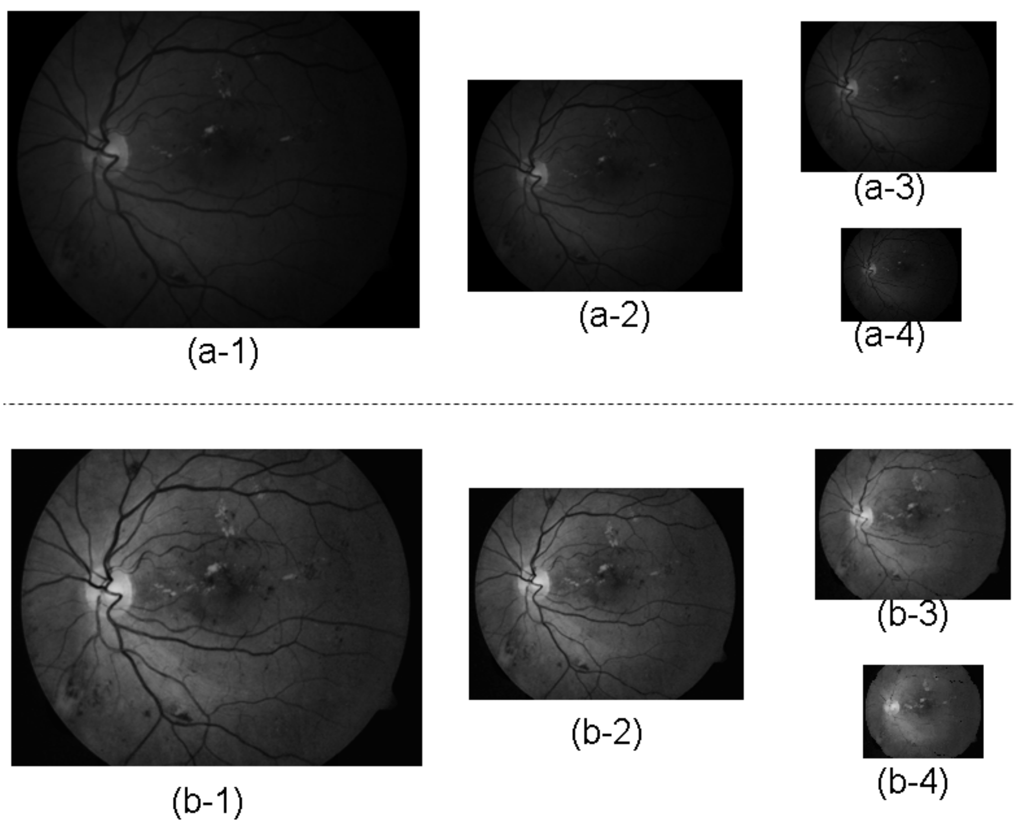


Figure 4. The green channel of a retinal image at level 2, 3 ,4 and 5 in the (a) conventional and (b) proposed extrema pyramidal decomposition

A conventional pyramidal decomposition based on averaging and sub-sampling is inadequate for OD detection as illustrated with an example in Fig. 4(a). Here, it can be seen that the averaging process dulls the entire image in effect lowering the height of the OD hill. In general, averaging and down-sampling operations result in large bright regions to disappear faster than darker regions. For locating hills, however, it would help to more or less retain the bright regions across several levels while accepting some loss in the darker regions. Hence, we need a method for pyramidal decomposition that will minimise darker regions at a much faster rate compared to the brighter regions. This calls for a controlled pyramidal decomposition technique. We propose the following solution. For a given image I_1 of size $M \times N$ a L-level decomposition is found by retaining extrema instead of average values: Since the OD regions are generally bigger and brighter regions,

$$I_k(m,n) = \begin{cases} \max\{g_{i,j}(m,n) & \text{if} \quad g_{i,j}(m,n) \leq t \\ \min\{g_{i,j}(m,n) & \text{otherwise} \end{cases}$$

where $g_{i,j}(m,n) = I_{k-1}(2m+i, \quad 2n+j)$ with $k = 2,3,...L$ and t is a suitable threshold, taken to be the global mean in our experiments. In an extrema pyramidal decomposition, the darker regions diminish in size at a much faster rate than brighter regions across the levels. This is illustrated in Fig. 4 (b). The extrema pyramid decomposition is able to retain OD locations even when they are less bright due to poor image quality.

At the lowest level of the pyramid, candidate OD locations are extracted by applying curvature based hill detection presented in [12]. At a hill point, the maximum principal curvature (MPC) has a magnitude maximum in all directions. Hence, candidate OD locations can be found by detecting local maxima of the MPC. We choose a light-weight numerical computation technique that we have proposed in [12] to compute the curvature. Let y = f(x) be any 1D function and the tangent at a point P on this function make an angle θ with the x−axis. The curvature estimate γ is defined as

$$\gamma(x) = \frac{\dfrac{d^2y}{dx^2}}{\left(1+\left(\dfrac{dy}{dx}\right)^2\right)^{3/2}}$$

γ(x) has been shown to be equal in scope and in detection sensitivity to the true curvature κ(x) for feature detection [12] and has been successfully used to detect ridges [13]. Given an image *I(m, n)* we can compute γ(x, αi), in the direction α_i from $I\alpha_i$ (m, n) which denotes the directional derivative of the image. If the curvature is computed in i = 1, ...M directions, hill-points in the image are points at which γ is a local maximum in all N directions. We use this fact to detect OD candidate points as follows: a point is declared as a candidate OD if the γ at that location is above a threshold value and maximum among its neighbours.

Next, these locations are mapped back to the original image. Performing the curvature computation only at the lowest level helps in reduce the computational burden and also ensure few candidate locations. Later, a confidence measure is derived for the identified location using domain knowledge related to OD (described in the next section).

3 Confidence measure computation and final OD detection

The OD is a region with the following common characteristics: (a) very bright area (b) high vessel density and (c) it is the convergence area for many vessels. These attribute of a retinal image are exploited to derive the confidence measure. In general, the individual attributes is not sufficient to decide final OD location. For instance, in poor/uneven illumination conditions or in the presence of bright lesions attribute-(a) (brightness) will not be effective. Furthermore, a poor focus and inappropriate view affects segmentation of necessary vasculature structure which makes attribute (a) and (b) ineffective. Thus, we combined all attributes to handle all possible variants of a retinal image.

Initially, at each candidate, confidence measure is assigned to zero and is further computed in the following manner. First, mean brightness value is computed within a pre-defined size neighbourhood. If computed mean value at a candidate is above a threshold then respective confidence measure is incremented by one. The threshold value is empirically estimated using average OD intensity value found across different dataset. Next, at each candidate point vessel density is derived using curvature information. A normalised sum of curvature values is computed within a pre-defined neighbourhood. A neighbourhood of size 50×50 pixels is chosen for our experiments. In the curvature map, vessel pixels get higher curvature value compare to non-vessel pixels. Since, OD is the convergence region of vessel network, candidate falls within OD will get high value of latter measure. We take a weighted sum of both the measures and choose final OD location having highest value of this summation. In our experiments, we have given high weight to the vessel density measure in order to handle bright pathologies cases because chances of vessel presence in a pathological region is very rare.

4 Experimental results

The proposed method has been evaluated on different datasets [9][10][11] and CRIAS (our own collection). Each dataset is divided into two categories (except DRIVE, which contains only normal images): level-1: normal and mild pathological images and level-2: images having high pathology. The parameters used by method are kept fixed across datasets and no specialised tuning is performed for individual dataset. The confidence measure is derived for each candidate OD obtained by method described in section 2. The quantitative results obtained from the proposed method are shown in table 1. First two rows in table 1 shows the candidate OD selection performance. The obtained performance demonstrates that characterisation of OD using topographical modelling is effective and accurate OD location is present in the detected candidate OD locations. The failure cases are due to partial and poor appearance of OD in an image.

Table 1: Candidate OD selection and final OD detection performance across different datasets. Numbers shown in brackets are total number of images and entries show percentage performance on the respective dataset.

	Dataset (no of images)	**STARE (81) %**	**DRIVE (40) %**	**DIAREDB-0 (130) %**	**DIAREDB-1 (89) %**	**CRIAS (228) %**
OD candidate selection	*Level-1*	100	100	99	100	97
	Level-2	92	--	92	100	93
Final OD detection	*Level-1*	83	97	93	84	74
	Level-2	64	--	23	60	48

The confidence measure is computed for each candidate OD (as explained in section 3) and candidate with high confidence measure is declared to final OD location. The detection is declared accurate if detected OD location falls in side the OD area. The detected OD location is later verified by a retina expert. Few successful OD detection results are shown in figure. 5. Last two rows in table 1 summarises the performance obtained. On an average, the final detection performance decreases compare to candidate OD selection. This is mainly due to weight assignment to different measures explained in section 3. For instance, in a bad illuminated image high weight should be given to vessel convergence attribute compare to the brightness based attribute to avoid false detection of a bright lesion as OD. The cases where major vessels are not visible, high weight should be given to the brightness attribute. An adaptive weighting criteria can be used to handle all possible variants and thus can improve overall detection performance.

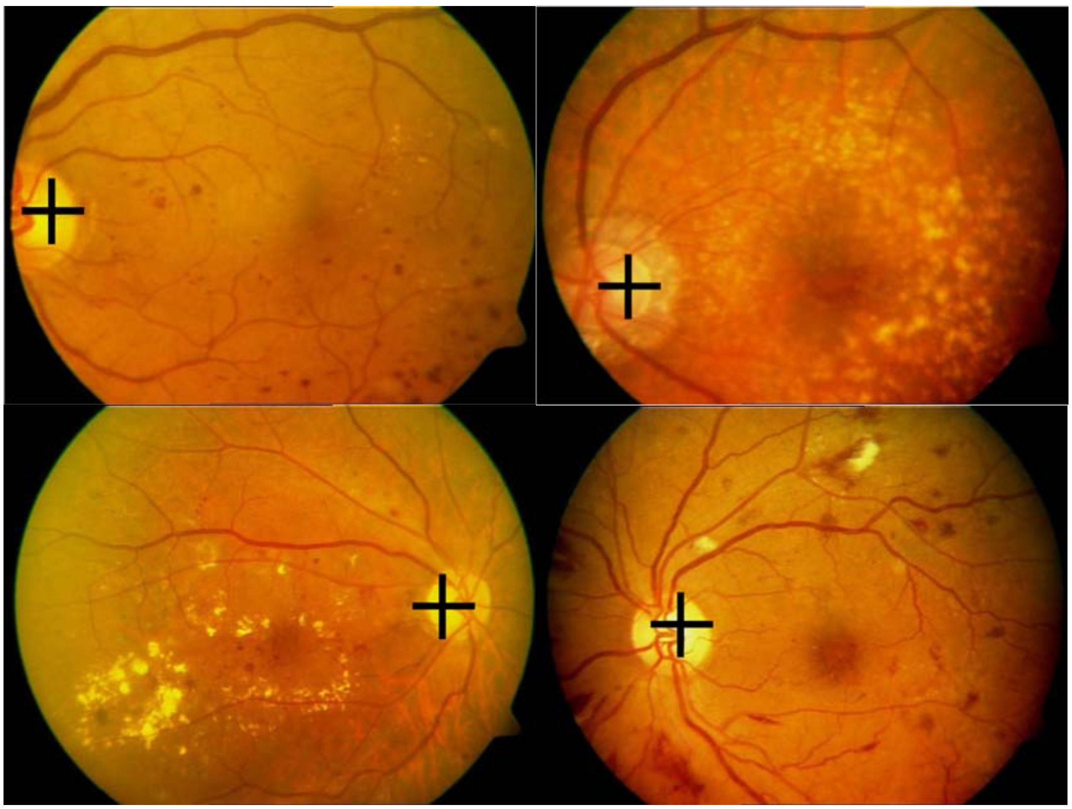


Figure 5. Few sample images of successful OD detection

5 Conclusions

In this paper, we present a topographical features based OD detection method which has been evaluated on different datasets. The proposed method is an hybrid approach which characterises OD using intensity and vessel structure based features. The curvature information is used to detect hill type topographical feature which inherently encodes intensity features. The obtained results show potential of topographical modelling in handling image variations found across datasets due to different cameras, different magnification and pigmentation. Moreover, derived confidence measure includes vessel convergence information which makes method robust to pathological images similar to a model-based approach. The parameters used in the proposed method can be customised for the individual dataset to get a high performance.

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