Appearance based Object Detection in Colour Retinal Images

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ABSTRACT

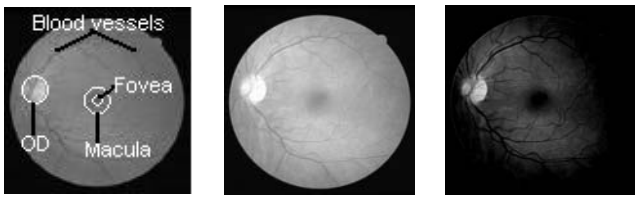
Extraction of anatomical structures (landmarks), such as optic disk (OD), fovea and blood vessels, from fundus images is useful in automatic diagnosis. Current approaches largely use spatial relationship among the landmarks' position for detection. In this paper, we present an appearance-based method for detecting fovea and OD from colour images. The strategy used for detection is based on improving the local contrast which is achieved by combining information from two spectral channels of the given image. The proposed method has been successfully tested on different datasets and the results show 96% detection for fovea and 91% detection for OD (a total of 502 and 531 images for fovea and OD are taken respectively).

***Index Terms*—** colour retinal image,contrast enhancement, fovea/optic disk detection

1. INTRODUCTION

Analysis of digital color fundus images (see [1] for a good review) encompasses extraction of structures which are present as part of anatomy (landmarks) or pathological lesions (signs of diseases). Landmarks include the OD (a bright region), fovea (a central part of a dark region known as the macula. See figure 1(a))) and blood vessel tree which are useful in automatic diagnosis [2]. Since the relative location of lesions with respect to these landmarks is critical in determining the medical urgency associated with a particular lesion type. Existing approaches for localisation of landmarks use the geometrical relation (model) among the landmarks. Specifically, the spatial relationship between the vascular structure,optic disk and fovea is modeled as a parabolic structure with the OD at the head of the parabola and the fovea located in line with the OD within the region enclosed by the parabola. The shape of the OD being roughly oval is another information used in its detection.

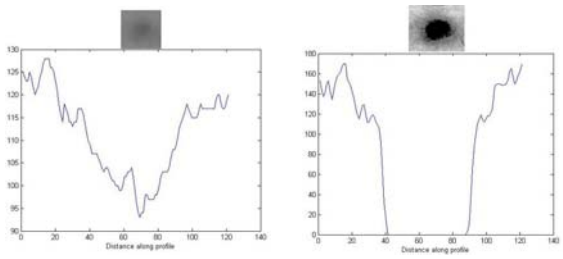
A pyramidal decomposition is used for OD detection in [3] and with a candidate region which potentially include the fovea being determined using its relative position with respect to the OD. Information from the vessel tree structure, extracted using a modified active shape model, and OD located via principal component analysis are used in [4]. A parabola is fit to extract the main arcade of the vessel structure from which OD and macula regions are located. The above mentioned methods are thus highly dependent on the accurate detection and segmentation of some of the structures in the overall detections scheme. This becomes difficult when there is only partial presence of structures (OD and vessels) and when lesions which are similar in appearance, are present. Landmark localization in a retinal image is a difficult problem also due to other practical factors such as large variations in image appearance due to poor/uneven illumination, imaging conditions and uneven noise which are addressed by general image enhancement techniques [5] [6] [7].



(a) (b) (c)

Fig. 1. (a) Intensity channel image I_i, (b) Red channel imageI_r, and (c) $I_i - (I_r)^c$ image

In this paper, we explore the possibility of localising structures of interest without employing a model of the underlying geometrical relationship. The aim is to develop a general approach that can be applied to detect a wide variety of structures. The detected result can be refined using post processing for good segmentation. Towards this goal, we propose a robust, appearance-based localisation method using different image channels. In the next section, we present the proposed method. The proposed method has been successfully tested on different and large sets of images collected from different sources. These are presented in the next section. We close with some directions for potential improvements.



(a) (b)

Fig. 2. Macula region along with 1D intensity profile in horizontal direction taken across macula region. (a) on intensity image and (b) on enhanced image obtained by proposed method.

2. PROPOSED METHOD

Let us assume that the landmark (object) to be localised in the given colour retinal image appears as a dark region. Several structures in the intensity component of retinal image I_i fit this description: fovea, blood vessels (tree like structure), haemorrhages (dark patches that can occur anywhere) etc. Each of these structures in turn have varying local contrast. For example, a magnified view of the fovea in Fig.2(a)), shows the contrast of the foveal region to be poor as the overall appearance of I_i is on the dark side. This is verified from the 1D plot of the cross sectional profile of this region, where the intensity transition from the fovea to the surround region is only 25 to 30 pixels. In short, the signal of interest is biased with a low intensity background illumination which itself can be slowly varying across the image due to non-uniform illumination. Similarly, OD is bright in appearance and occurs with varying contrast ranging from low to high. We wish to formulate detecting such structures from a given image by formulating it as a signal detection problem. The strategy we adopt is to develop a technique for boosting the signal to noise ratio (SNR) for the structure of interest and then perform the detection using simple thresholding and classification.

In the context of detecting dark structures, the aim is to deepen the valleys representing such structures. A contrast enhancement technique applied globally or adaptively will not yield good results as the choice of parameters such as the region size in the adaptation stage is crucial for good results across a large set of images of varying quality. This can be seen from the results shown in Fig.3(column a), of applying contrast limited histogram equalisation (CLAHE) [8] followed by a global linear contrast stretch to the images of different quality in Fig.3(column b)).

The fovea appears well contrasted Fig.3 (b-1) while it is barely visible in Fig.3 (b-2). This point needs inclusion of information about the background of the structure of interest in its detection. By treating the background broadly as *noise*, we propose an alternate solution wherein SNR boosting is achieved by combining information across two channels of the colour retinal image. The second channel that is appropriate is the red channel (I_r) as it represents the reflectance component in retinal images. I_r by virtue of capturing the reflectance component, will naturally provide information about non-uniform illumination which is useful in the SNR boosting. This point has been exploited to perform illumination correction, via histogram matching with the green channel image, prior to vessel detection in [5]. The additional benefit in using the red plane is that it also contains the dark objects of interest albeit at a much weaker level (lower SNR than in I_i) which can be exploited as explained below.

Let us consider projecting the original colour image I into two appropriate planes I_a and I_b such that both I_a and I_b contain the signal of interest, while the latter is dominated by noise. A simple subtraction of I_b from I_a will remove the noise but will also weaken the signal in the output. If instead we complement I_b and perform a relative subtraction operation, the signal gets enhanced while the noise is suppressed (shown in Fig. 1(c)). In a digital image, subtraction will result in clipping of negative pixel values which can weaken the global contrast of the output image. This is addressed by improving the contrast of the images before the relative subtraction operation. The images in Fig.3 (column (c)) show the effective improvement in the SNR of objects (dark) of interest and the overall contrast. From these images it is seen that the net effect is also to retain the background while boosting local contrast which is not achieved by applying only traditional contrast enhancement. The SNR boosting is verified in the deeper and steeper valley profile of the fovea region shown in Fig.2(b) in comparison with the original profile in Fig.2(a).

Based on these observations, we now propose a general method for detecting structures based on their appearance from a given retinal image. Let a structure be denoted as S:

1. *Apply contrast enhancement to I_i and I_r. Let the corresponding outputs be I_A and I_B.*
2. *Calculate $I_s = I_A - (I_B)^c$*
3. *Binarise by applying a fixed global threshold for filtering plausible candidates for S.*
4. *Apply prior knowledge about the structure of interest to correctly detect S.*

Theoretically, step 2 will enhance common regions in image I_a and I_b. We will next showcase this method by developing a method for detecting the fovea and OD, which are two important structures of interest in a retinal image. Since the OD is a bright structure, the images have to be negated before applying the above technique for its detection.

3. EXPERIMENT RESULTS

We have tested the proposed method on two publicly available retinal datasets STARE [9], DRIVE [10] and on a dataset

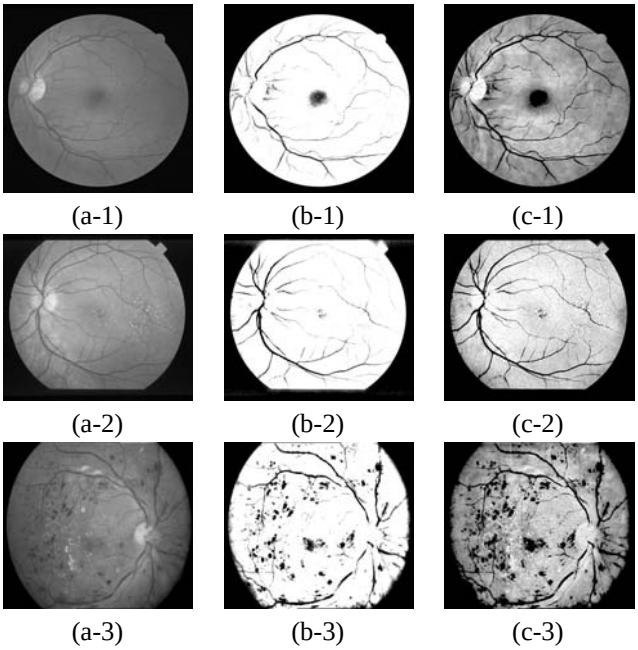


Fig. 3. Column (a) shows intensity image I_i of sample images, Column (b) shows corresponding images obtained by applying CLAHE followed by contrast stretching, and Column (c) shows corresponding images obtained by proposed method using common set of parameters.

collected by us (referred as CRIAS). The motivation in using different datasets is to evaluate the performance of the proposed method on images of different quality due to different cameras and high/low pigmentation levels found in Asian /Caucasian populations. The number of images used from each dataset depends on the structure detected and it was based on presence/absence of the target structure. Each image dataset is classified into level-1: normal and level-2: pathological/poor quality colour fundus images (except the DRIVE dataset which have only normal images). Few sample level-1 and level-2 images are shown in row-1 and row-2 of fig. 4 respectively. The variations due to different cameras and pigmentation levels can be seen in the images. A common algorithm is used (presented in section 2) for fovea and OD detection with a common set of parameters. A window size of $8x8$ is used for CLAHE and a global fixed threshold is empirically computed and used across all datasets. Some candidate regions are obtained after thresholding (step-3) from which the structure of interest is selected using suitable criteria. In this work, we have used size and aspect-ratio as criteria to select the fovea/OD. The obtained results have been visually verified by a retina expert.

For OD detection, the input image was inverted to model OD as a dark object. Figure 4 shows OD detection results on few sample images. It can be seen that the method successfully detects OD in images with pathology which have similar

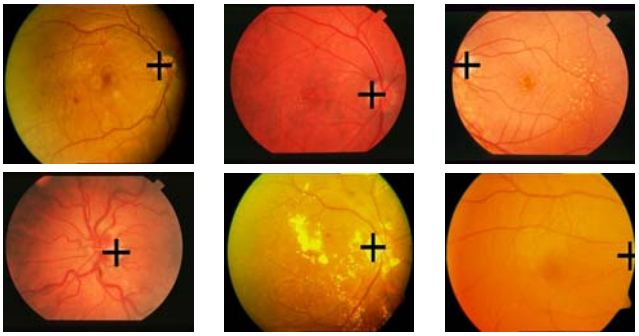


Fig. 4. Results of OD detection on level-1 (first-row) and level-2 (second-row)images

bright appearance (second row fig. 4) even with our simple selection criteria. The overall performance of OD detection is summarised in table 1(c). The proposed method shows a good performance (94.4%) on level-1 images and satisfactory performance (87.22%) on level-2 images.

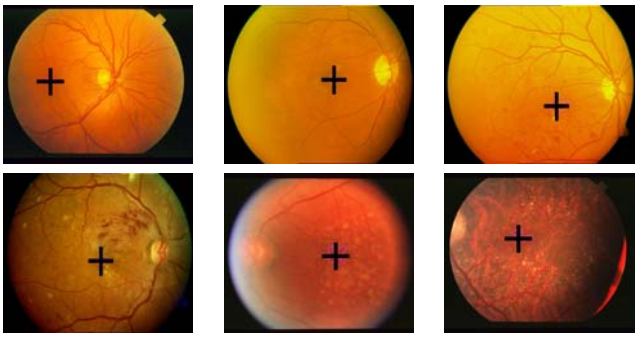
Fig. 5 shows sample results of fovea detection. The images demonstrate the method to be fairly robust to presence of pathologies and bad illuminated regions have similar appearance to fovea (level 2). The overall detection performance is summarised in table 1. Overall, the detection rate is 100% and 61.69% on DRIVE and CRIAS respectively whereas on STARE dataset the performance is not satisfactory (33.3% even for level-1). It was found that the fovea was largely absent in the red channel images which is highly saturated in this set(due to different retinal pigmentation). It appeared that a simple size and aspect-ratio is inadequate to help select accurate fovea region from competing ones due pathologies and ill-lit regions. In order to improve the overall detection performance (on level- 1 and 2), a top-hat transformation was applied on the red channel (in lieu of complement) before subtraction operation to mainly address the poorly illuminated regions. As seen from the table 1,(b) this results in a significant improvement in the overall performance. Analysis of the failure cases revealed the culprit to be the selection stage which used simple criteria. It was found that the the right candidate was the second or third best candidate in majority of the cases whereas our selection stage chose the top rank. Some failure cases are shown in Fig. 6 for both OD/fovea detection.

4. CONCLUSION

In this paper, we presented an appearance-based method for detecting fovea and OD using a novel dual-channel based contrast enhancement method. This method gives a very promising performance on different datasets (with variations in cameras and pigmentation and illuminations). The performance of the proposed method can be significantly improved by incorporating domain knowledge about the structure of

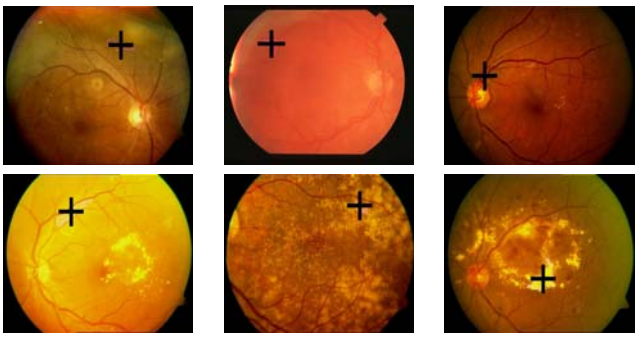
	a:Fovea Detection			b:Optimised Fovea Detection			c:OD Detection		
	level-1	level-2	Average	level-1	level-2	Average	level-1	level-2	Average
DRIVE	100%	-	100%	100%	-	100%	94.87%	-	94.87%
STARE	33.33%	25.00%	29.48%	92.85%	72.22%	83.33%	80.95%	77.04%	78.64%
CRIAS	80.44%	35.97%	61.69%	99.55%	98.17%	98.97%	96.86%	89.63%	94.34%
Average	76.15% (230/302)	34.00% (68/200)	59.36% (298/502)	98.67% (298/302)	93.50% (187/200)	96.61% (485/502)	94.40% (287/304)	87.22% (198/227)	91.33% (485/531)

Table 1. fovea detection and OD detection performance on level-1 and level-2 images.



(a) (b) (c)

Fig. 5. Fovea detection on level-1 (first row) and level-2 (second row) images



(a) (b) (c)

Fig. 6. Failure cases of fovea (first row) and OD (second row) detection

interest in the selection criteria. A simple way to do it is to combine the results of fovea and OD detection and verify their spatial relationship before a final selection. The proposed method has potential in segmenting pathologies with similar appearance to OD/fovea. Fig. 7 shows one such example where drusen are detected using OD detection method.

5. ACKNOWLEDGEMENT

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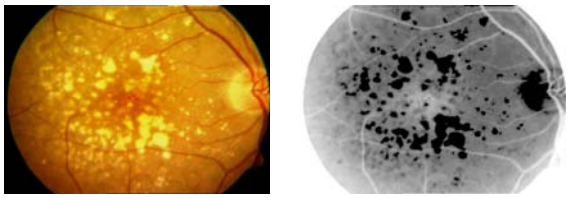

(a) (b)

Fig. 7. (a)Color retinal image (b) Enhanced drusen regions using OD detection

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