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Automatic Detection of Anatomical Structures in Digital Fundus Retinal Images

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Abstract

This paper proposes a novel system for the automatic detection of important anatomical structures such as the Optic Disc (OD), Blood Vessels and Macula in digital fundus retinal images. The novelty is in extraction of blood vessels and localization of macula. OD localization is done using Principle Component Analysis (PCA) followed by an active contour based approach for accurate segmentation of its boundary. A morphology based approach is proposed for Blood Vessel Detection (BVD). Macula is identified by combining BVD with the property that it is the darkest area in the vicinity of OD. The proposed method is tested on a set of 100 images and the results demonstrate the accuracy of the proposed system.

1. Introduction

Retinal Image Analysis is a key element in detecting retinopathies in patients. It assists in the automatic detection of pathologies such as diabetic retinopathy (DR), macular degeneration, and glaucoma. Optic Disc (OD), macula and retinal vasculature are all important anatomical structures in the retina. The OD localization and segmentation is a crucial task in an automated retinal image analysis system. It is required as a prerequisite for the detection of exudates and also helps in macula detection, as macula is the darkest area in the neighborhood of OD. Blood Vessel Detection (BVD) is an essential step in medical diagnosis of fundus images as it aids in the diagnosis of ocular diseases. Other applications of retinal vasculature extraction include the treatment of age-related macular degeneration, registration algorithms and personal identification in security applications. Macula is highly sensitive region of the retina responsible for detailed central vision. Macular oedema is a special case of DR caused by the leakage of blood vessels in the macula region. Macular oedema can be treated with laser if detected early enough. Identifying the macula region assumes utmost importance as a first step in the detection of macular oedema.

In [1] OD is localized as the region with maximum intensity variation from its neighborhood. [2] employs pyramidal decomposition and Hausdorff-based template matching for localization and segmentation of the OD. Our approach for OD segmentation is inline with [3] which localizes OD by Principle Component Analysis (PCA) and detects boundary by Gradient Vector Flow (GVF) snakes.

A survey of vessel extraction techniques and algorithms is reported in [5]. Design of 2-d matched filters for BVD is detailed in [6]. This approach is computationally expensive due to the large size of the convolution kernel. A supervised multilayer perceptron neural network is employed for BVD in [1]. The inputs for the network are derived from PCA and this method requires manually labeled images for training. In [2] a tracking-based approach with recursive dual edge tracking and connectivity recovering is applied for BVD. This procedure has been tested only on 5 images. The method for BVD in [4] is based on quad-tree decomposition and post-filtration of edges. This approach does not address the problem of noise reduction. In this paper we propose a method based on morphology for BVD.

In [1] macula is determined by matching correlation together with the characteristic of the fovea that it is the darkest area in the vicinity of the OD. Macula is detected in [2] by locating the darkest pixel in the coarse resolution image following an a-priori geometric criteria based on eye's anatomy. The method proposed in this paper for macula detection masks out the vessel pixels using the result of BVD and identifies the macula by finding the darkest cluster of pixels near the OD.

2. Proposed Method

The method is carried out in the various stages. Figure 1 shows a schematic diagram of the proposed method.

2.1 OD Segmentation

The method for the implementation of PCA for OD localization is as follows. The pixels in the test image with the highest 5% intensity level and hue value in the yellow range are identified as candidate regions. A clustering mechanism is used to group them into clusters, abandoning clusters in which pixel count falls below a threshold limit.

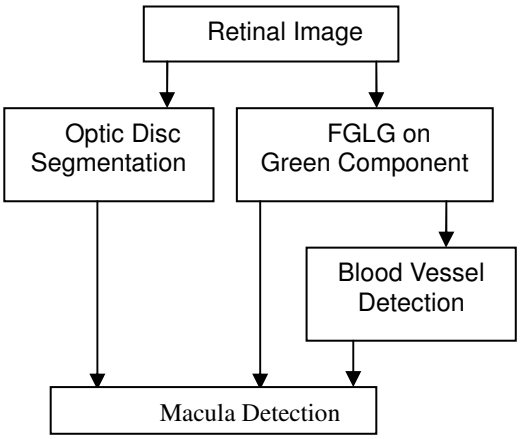


Figure 1. Schematic diagram of the proposed method

The remaining clusters qualify as candidate regions for further processing. The approach includes calculating the eigen vectors of the covariance matrix of the training images and constructing "disc space" specified by the eigen vectors. The candidate image patch is projected on to the disc space and the distance between retinal image and its projection is calculated. The candidate with the minimum difference is identified to be the OD amongst the candidates and the centre of OD located at the point with the minimum distance. Sample results are shown in figure 2.

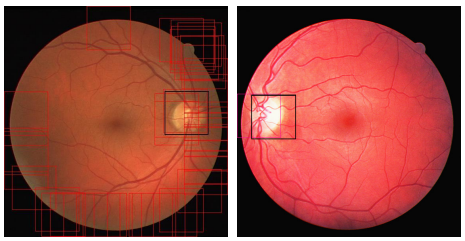


Figure 2. Results of OD Localization. The Black square shows the localized OD.

Once OD is localized the homogenization of the OD region is done and the boundary of OD region is found using Gradient Vector Flow (GVF) snakes [3]. Figure 3 displays a couple of results.

2.2 Gray level grouping for contrast enhancement.

There is degradation in quality of contrast as we move from the centre towards the boundary of fundus image. Also, Blood vessels usually have poor local contrast [6]. Hence contrast enhancement is a necessary prerequisite. The green channel of the RGB space is chosen for this purpose because blood vessels appear most contrasted in this channel.

Conventionally, methods such as histogram equalization, adaptive histogram equalization and histogram specification are used for contrast enhancement. For our purpose we make use of Gray Level Grouping (GLG) [8] as it is an automatic method unlike histogram specification, and shows improved performance over existing methods.

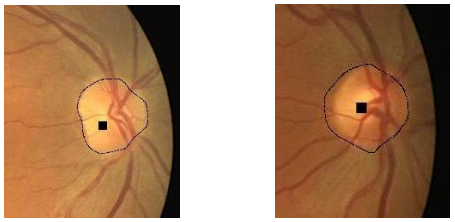
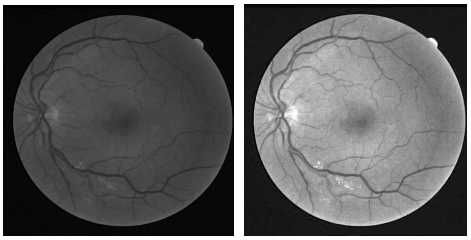


Figure 3. Result of OD Boundary Segmentation. The black dot represents the approximate centre of the OD.

The basic procedure for Gray Level Grouping [8] is as follows.

- Firstly, the histogram components of the input image are grouped in to a number of gray level bins according to their amplitudes.
- These groups of histogram components are redistributed over the grayscale, so that each group occupies a grayscale segment of the same size as the other groups, thereby spreading the concentrated histogram components spread and enhancing the image contrast.
- Ungrouping the previously grouped gray-levels and mapping the gray-level values of the pixels in the input image to the desired values in the output image is performed.

A variation of GLG called Fast Gray Level Grouping (FGLG) has been applied on the images and Figure 4 shows a sample result.



(a) (b)

Figure 4. FGLG for contrast enhancement: (a) green channel of a test image. (b) image after contrast enhancement

2.3 Blood Vessel Detection (BVD)

Our method for BVD is based on morphology and is applied on the contrast enhanced images. Some basic morphological operations [7] are defined below.

Let $D_f \subseteq Z^2$ and T= $\{t_{\min},\ldots,t_{\max}\}$ be an ordered set of gray levels. A gray level image f can be defined as a function $f : D_f \subseteq Z^2 \rightarrow$ T= $\{t_{\min},\ldots,t_{\max}\}$. Let B be a subset of Z^2 and s $\in$ N a scaling factor, the morphological operations are defined as follows.

- Erosion: $[\varepsilon^{(sB)}(f)](x) = \min_{b \in sB} f(x+b).$
- Dilation: $[\delta^{(sB)}(f)](x) = \max_{b \in sB} f(x+b).$
- Opening: $\gamma^{(sB)}(f) = \delta^{(sB)}[\varepsilon^{(sB)}(f)].$
- Closing: $\phi^{(sB)}(f) = \varepsilon^{(sB)}[\delta^{(sB)}(f)].$

Our method for blood vessel detection uses top-hat

transform as follows. Let g represent the green channel of the test image after contrast enhancement. Firstly, blood vessels are eliminated by a closing operation. A square structuring element $s_1 B$ is used for the purpose. s_1 is chosen such that $s_1 B$ is larger than the maximal width of blood vessels.

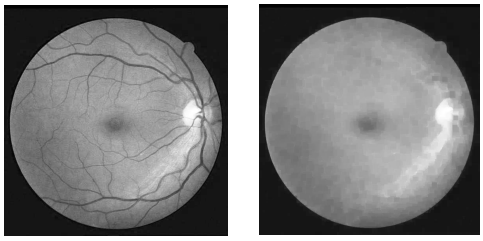
$$h_1 = \phi^{(s_1 B)}(g). \quad (1)$$

Figure 5 shows a sample result of closing operation.

Then image subtraction is performed, where the image g is subtracted from the closed image h_1.

$$h_2 = h_1 - g. \quad (2)$$

Since blood vessels are relatively darker compared to the background, the values at locations of vessel pixels in h_2 will be higher compared to the values at locations of non vessel pixels. Hence, thresholding h_2 at level t_1, where t_1 is chosen appropriately extracts blood vessels. Post processing is performed for reduction of noise. Small isolated regions of pixels misclassified as blood vessels are removed using connected component labeling choosing size as criteria. Figure 6 shows a result of our approach against the one in [4].



(a) (b)

Figure 5. Result of closing: (a) input image. (b) image after morphological closing.

2.4 Macula Detection

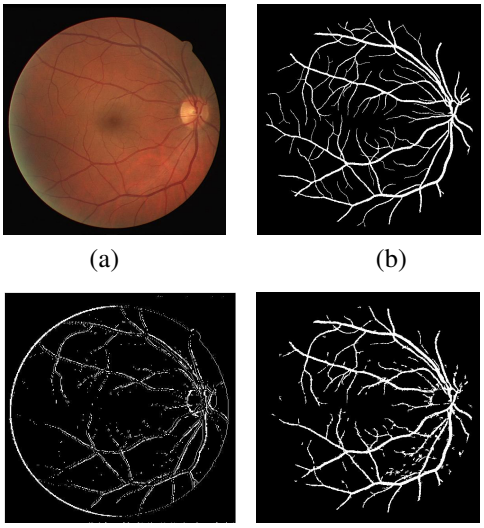
Fovea is the central part of the macula that provides the sharpest vision. It is said that the centre of the fovea is usually located at a distance of approximately 2.5 times the diameter of the optic disc, from the centre of the optic disc [1]. As OD is already localized and segmented, approximate diameter of the OD is found from the boundary of OD. Let the diameter of OD be d.

The proposed method for macula detection is as follows: Firstly the Region Of Interest (ROI) is found from the geometric criteria based on eye's anatomy. The ROI contains only those pixels in the image whose radial distance r from the center of OD satisfies the following equation.

$$(1.5 \times d) < r < (3.5 \times d). \quad (3)$$

The algorithm assumes that it is known before hand whether the image is centered on the macula or not. If the image is centered on the macula then ROI contains pixels that are oriented towards the centre of the image and satisfy (3). Otherwise ROI contains all the pixels in the image which satisfy (3). Figure 7 shows ROI for a sample image. Pixels which do not belong to the ROI are marked white.

The result of BVD is used to mask out vessel pixels in the region of interest. Then we determine the darkest 1% pixels in the ROI. These pixels are clustered together , and the largest cluster is localized as macula. A circle with diameter equal to twice the diameter of OD is drawn to represent the macula region (figure 7).



(a) (b)

(c) (d)

Figure 6. Result of BVD: (a) test image. (b)manually labeled image.(c) result of applying the approach in [4] (d) Result of our approach.

3. Experimental Setup, Results and Discussion

The proposed method is implemented in MATLAB on a P4 machine. The algorithm is tested on a dataset of 100 images. This dataset includes 40 images from the DRIVE database. For the PCA approach the hue range for candidate regions is [0.075 0.17] and the threshold limit is 20. For morphological closing a square structuring element of size 11 is chosen. The threshold t_1 is set at 20.

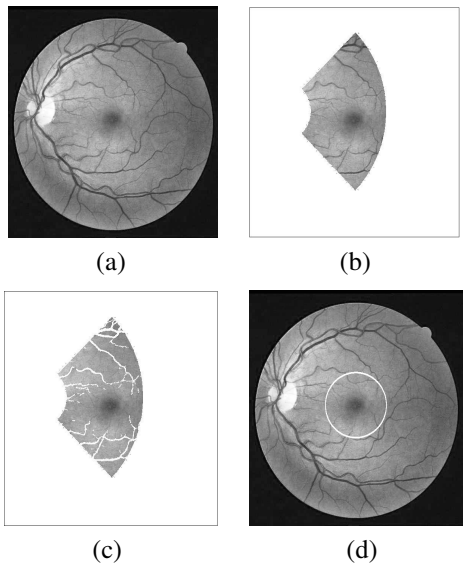
The BVD algorithm is tested on 100 images and result of our algorithm on a sample image in comparison with manually labeled data is shown in figure 6.These 100 images include 20 images from the DRIVE test set and 20 images from STARE database. When tested on the DRIVE test set, the proposed algorithm achieved sensitivity and specificity of 70.14% and 96.44% respectively. When tested on the STARE images the proposed method achieved sensitivity and specificity of 64.34% and 97.08% respectively. The proposed algorithm for macula detection, when tested on 100 images resulted in a success rate of 96%.

Figure 8 shows results of our approach for the automatic detection of anatomical structures in the retina.

4. Conclusions

A novel system for the automatic detection of important anatomical structures such as OD, macula and blood ves-

sels has been proposed in this paper. Robustness and accuracy of the system have been evaluated on a database of 100 images. The results are encouraging and these methods contribute to our overall goal of development of a system for the automated screening of Diabetic Retinopathy in medical camps. Our research work is continuing to evaluate the robustness of the algorithms over a large number of images. Our future work will focus on prediction of DR in patients based on the changes in the caliber of retinal blood vessels.



(a) (b) (c) (d)

Figure 7. ROI detection: (a) test image. (b)Result of ROI detection.(c) masking out the blood vessels (d) Result of macula detection.

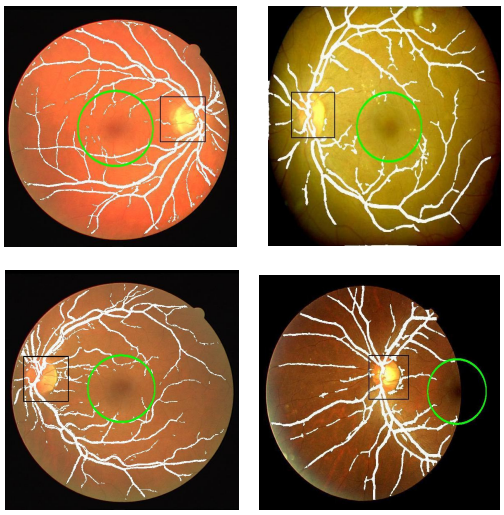


Figure 8. Detection of anatomical structures in the retina. The black square represents the localized OD, green circle represents the macula region and the blood vessels are marked white.

Acknowledgements

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References

[1] C. Sinthanayothin, J. Boyce, H. Cook, T.Williamson, "Automatic Localization of Optic Disc, Fovea, and Retinal Blood Vessel from Digital Colour Fundus Images," Br. J. Ophthalmol., 1999,83,pp.902-910.

[2] L. Gagnon, M. Lalonde, M. Beaulieu, M.-C. Boucher, "Procedure to Detect Anatomical Structures in Optical Fundus Images", Proc. SPIE Med. Imaging: Image Processing, vol.. 4322, pp.1218-1225, 2001.

[3] G. Vijaya Saradhi, S.Balasubramanian, V.Chandrasekaran, "Performance Enhancement of Optic Disc Boundary Detection using Active Contours via Improved Homogenization of Optic Disc Region.," Proceedings of the International Conference on Information and Automation, Dec 2006.

[4] Dua S,Kandiraju N, Thompson HW, "Design and Implementation of a Unique Blood-vessel Detection Algorithm towards Early Detection of Diabetic Retinopathy," Proceedings of the IEEE International Conference on Information Technology,Vol I, pp. 26-31, 2005.

[5] Cemil Kirbas, Francis K. H. Quek., "Vessel Extraction Techniques and Algorithms: A Survey," Third IEEE Symposium on Bioinformatics and Bio Engineering, Mar 2003.

[6] Chaudhuri, S., Chatterjee, S., Katz, N., Nelson, M., and Goldbaum, M., "Detection of Blood Vessels in Retinal Images using Two Dimensional Matched Filters", IEEE Trans. Med. Imag., vol. 8, 1989, pp. 263-269.

[7] T. Walter, J. C. Klein, P.Massin, and A.Erginay, "A Contribution of Image Processing to the Diagnosis of Diabetic Retinopathy –Detection of Exudates in Color Fundus Images of the Human Retina," IEEE Trans. Med. Imag., vol.21, no. 7, pp. 1010-1019, Jul.2001.

[8] Zhi Yu Chin, Besma R. Abidi, David L.Page, Mongi A. Abidi, "Gray-Level Grouping (GLG):An Automatic Method for Optimized Image Contrast Enhancement – Part I : The Basic Method," IEEE Trans. Image Process., vol. 15, no.8, pp. 2290-2302, Aug. 2006.