Optic Disc Segmentation in Retinal Images

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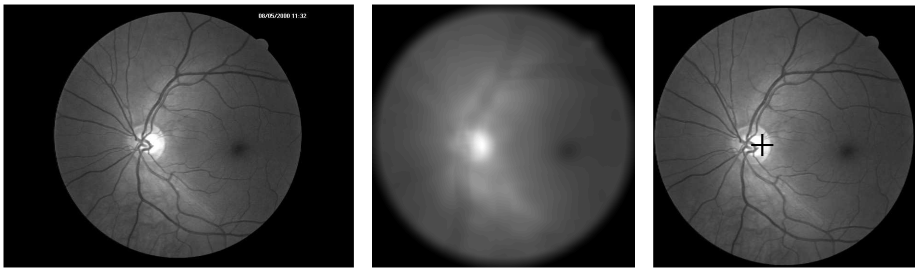
Abstract Retinal images give unique diagnostic information not only about eye disease but about other organs as well [1]. To give the physicians a tool for objective quantitative assessment of the retina, automated methods have been developed. In this paper an automated method for the optic disc segmentation is presented. The method consists of 4 steps: localization of the optic disc, nonlinear filtering, Canny edge detector and Hough transform. The results have shown that the algorithm is very robust. The localization was 97% successful and the segmentation 82%.

1 Introduction

Retinal images give us unique information not only about retinal or ophthalmic diseases but also about cerebrovascular and other diseases [1]. To support ophthalmologists in often time-consuming and hardly reproduceable evaluation of the retina and to give them tools for the quantitative assessment, automated methods for a retinal analysis and assessment have been developed. One of the important steps in the retina analysis is the optic disc segmentation. We present an automated method for the optic disc segmentation. The method is a part of our project for automated retinal arterio-venous (A/V) ratio calculation for detection and monitoring of vascular disease. The A/V ratio calculation is based on the propositions described in [2] and consists of establishing the measurement zone based on optic disc segmentation, vessel segmentation, classification of vessels as arteries and veins and vessel diameter measurement.

There are methods for detecting the optic disc based on segmented vessel network [3]. There are also a large number of tracking-based methods for vessel segmentation usually starting from the optic disc [4]. The proposed method does not depend on segmented vessel network and can be used for initialization of starting points of some tracking-based methods as well.



(a) (b) (c)

Fig. 1. Localization of the optic disc: (a) green channel of the original retinal image; (b) averaging with the mask 31×31; (c) result of the localization (black cross).

2 Method

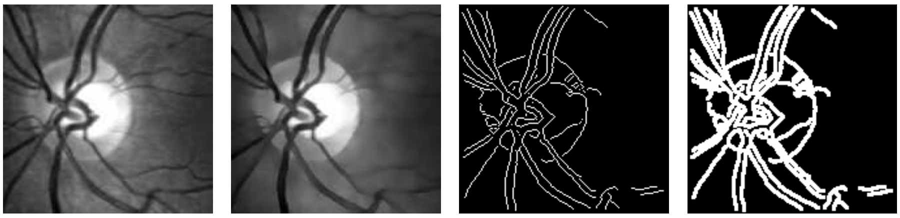
The method has been developed for images of a non-mydriatic retinal camera. The size of the images is of 760×570 pixels, 24 bits per pixel (standard RGB). The green channel (Fig. 1(a)) was only used for calculations described in the following.

2.1 Optic disc localization

The first step of the algorithm is a rough localization of the optic disc and defining region of interest (ROI) (Fig. 2(a)). The purpose is to reduce the computational complexity in further steps. The optic disc is characterized by gray values, which are brighter than the background values. Therefore the optic disc can be localized (Fig. 1(c)) by detecting maximum gray values in an image preprocessed by averaging with a mask of size 31×31 (Fig. 1(b)). The image is preprocessed because background artifacts (either caused by an imperfection of the camera or physiological properties of the retina) can cause false localization. The size of the ROI was set to 130×130.

2.2 Nonlinear filtering

Because images contain noise making edge detection of the optic disc difficult, a method for noise reduction has to be applied. Classical methods such as averaging or median filtering did not give satisfying results. An algorithm from the family of nonlinear filtering techniques [5] was tested and it gave excellent results (Fig. 2(b)). The algorithm reduced noise and at the same time preserved edges. The problem was described by the weak membrane model. The model is analogous to the behavior of a rigid membrane. Suppose a membrane is fitted to the



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

Fig. 2. Filtering and edge detection: (a) defining ROI; (b) nonlinear filtering; (c) result of Canny edge detector; (d) dilatation of the image (c).

gray values of the image: If the local difference in gray values is sufficiently large, the membrane is torn and an edge is introduced. At the same time, small noisy discontinuities do not tear the membrane therefore smoothness of the regions is preserved. The model leads to a set of generally nonlinear equations solved in our case with the mean field annealing method.

2.3 Canny edge detector and Hough transform

Filtering is followed by edge detection. The best results were achieved with Canny edge detector (thresholded responses of the Canny operator) (Fig. 2(c)). The detected edges correspond not only to optic disc margins but also to blood vessel borders. Since the optic disc is a circular structure, an algorithm for a circle detection was expected to solve the problem. The Hough transform for circle equation was applied. Because the optic disc margin does not exactly correspond to a circle, a dilatation was applied to the Canny edge image (Fig. 2(d)). The Hough accumulator is a 2-D matrix, which is filled (for a given fixed radius) with potential candidates of circle central points for each nonzero pixel of the Canny image after dilatation. The values in the Hough accumulator are equal to the number of border points of circles (with the given radius) in the image. For each radius, starting with a value greater than the expected radius of optic disk and stepwise decreasing until a minimum radius is reached, the Hough accumulator is (cleared and) filled. The algorithm is stopped when the maximum of the Hough accumulator for given radius is greater than 60% of border points of the ideal circle. The position of the maximum is supposed to be the center of optic disk. If the maximum is less than 60%, the Hough accumulator is erased and filled for the next radius. If no maximum is found and the minimal radius is reached, a message is issued and the calculation stopped. Hough transform gives the center and radius of a circle approximating the border of the optic disk (Fig. 3). The implementation of the method and all calculations were carried out in MATLAB.

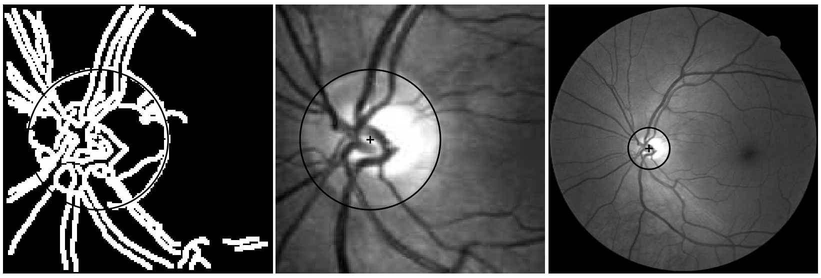


Fig. 3. Result of the optic disc segmentation.

3 Results

The method was tested on 263 different images with various image quality from the right and the left eye of about 130 patients. 6 images were automatically excluded from the calculation by the algorithm; 2 of them because they were over-exposed and 4 because of bad image quality disabling Hough transform to work properly. The optic disc localization was 97,3% (254 of 261 images) successful judged by visual inspection. Correct localization means that the coordinates of the detected position of the optic disc lies inside of the optic disc. The contour of the optic disc was 81,7% (210 of 257 images) correctly segmented where the criterion of correctness was the visual inspection by an ophthalmologist.

4 Conclusions

We have developed a robust method for optic disc segmentation. The results have shown that the method is robust and very suitable for our project by establishing measurement zone for A/V ratio calculation and also for some tracking-based methods by automatic initialization of starting points.

References

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