Automated detection of optic disc location in retinal images

Carmen Alina Lupascu
Dipartimento di Matematica e Applicazioni
Università degli Studi di Palermo
Palermo, Italy
lupascu@math.unipa.it

Luigi Di Rosa
Clinica Oculistica
Policlinico Universitario Paolo Giaccone
Palermo, Italy

Domenico Tegolo
Dipartimento di Matematica e Applicazioni
Università degli Studi di Palermo
Palermo, Italy
domenico.tegolo@unipa.it

Abstract

This contribution presents an automated method to locate the optic disc in color fundus images. The method uses texture descriptors and a regression based method in order to determine the best circle that fits the optic disc. The best circle is chosen from a set of circles determined with an innovative method, not using the Hough transform as past approaches. An evaluation of the proposed method has been done using a database of 40 images. On this data set, our method achieved 95% success rate for the localization of the optic disc and 70% success rate for the identification of the optic disc contour (as a circle).

1. Introduction

The optic nerve is one of the most important structure in the human visual system. The vessels of the retina emanate through the optic nerve, supplying the upper layers of the retina with blood. The optic nerve also transmits visual information from the retina to the brain.

The optic disc (henceforth OD) is the point at the inside back of the eyeball where the fibres of the retina converge to form the optic nerve. The OD in a healthy retinal image usually appears as a bright yellowish and circular shape which is partly covered with vessels. Due to the luminance or the blurriness the optic disc may appear different from image to image. The OD-appearance may also be affected by diseases (may be covered by too many vessels or it may be bigger or smaller than normal). So the optic disc in retinal images varies in appearance, size and location.

The identification of the position and the shape of the optic disc in the retinal images is very important for the diagnosis of the eyeball’s diseases like optic atrophy, optic neuritis, papilledema, ischemic optic neuropathy, glaucoma and for more general diseases of the human body (diabetes, arterial hypertension, etc.).

1.1. Related Work

In the literature many techniques have been used to automatically detect the position of the optic disc in retinal images. Sinthanayothin et al. [9] located the optic disc by identifying the area with the highest variation in intensity of adjacent pixels. After the local contrast enhancement, the maximum value of the mean variance image is chosen as the OD-center.

But as the shape of the optic disc is very important just the identification of the OD-center is not enough. Hence, Park et al. [8] identify the optic disc as the round area with brightness. First the algorithm searches for several areas with high intensity variation and then selects all rounded areas from the several areas (the roundness is measured with a special method which requires 360° traces of the work-piece made with a turntable-type instrument or a stylus-type instrument. A least squares fit of points on the trace to a circle define the parameters of non circularity of the work-piece). Next, with the use of Hough transform on the edges of rounded areas, the OD-contour is estimated as a circle. The OD of the image is selected as the circle which has higher intensity.

In the presence of retinal diseases, assuming that the OD is the area which has higher intensity is not enough for the identification of the OD location [10]. Areas with high...
intensity may include diseased areas and possible bright, noisy spots. For example, the brightness of some lesions of the retina called drusen, overlaps the brightness of the optic disc. Also a retina exhibiting choroidal neovascularization and sub retinal fibrosis presents bright circular lesions that appear similar to the optic disc. Hence, Hoover and Goldbaum [3] use the fuzzy convergence to determine the origin of the vessel network. In this way the OD location is correctly detected even in the presence of spots brighter than the optic disc. The authors use multiple vessel segmentations of the same image in order to reinforce the detection of convergent points. The input of the algorithm is a binary segmentation of the blood vessels and the output is a convergence image, which is thresholded to identify the strongest point(s) of convergence. In the absence of a strong convergence this method identifies the optic nerve as the brightest region in the image after illumination equalization.

Li and Chutatape in [5] propose another method in order to identify better the OD location even in the presence of spots that are as bright or even brighter than the optic disc. They cluster the brightest pixels (the pixels with the highest 1% gray levels) in the intensity image and, to these candidate regions, a PCA (Principal Component Analysis) is then applied. The algorithm calculates the eigenvalues from the training images, projects the new retinal image to the space specified by the eigenvectors and then calculates the distance between the retinal image and its projection. The center of optic disk is located at the point with the minimum distance. PCA is applied to each pixel in the image, so the computation is time consuming.

Past works, [9, 3, 4] on the OD has mainly focused on locating it’s center. Lalonde et al. [4] localized the optic disc using template matching based upon Hausdorff distance and using also pyramidal decomposition.

Most reported works do not identify accurately the OD boundary (most of them estimate the OD boundary with a circle). Mendels et al. [6] processed first the image grey level mathematical morphology to remove blood vessels. Then a snake was manually placed around the OD and allowed to evolve onto its boundary. A. Osareh et al. in [7] improved this method by using a simple template matching approach to estimate the OD center position. This allows the automatically initialization of the snake. They also use color mathematical morphology on the original color image to improve the boundary localization.

One important obstacle in the detection of the optic disc boundaries is vessel occlusion. In the last recent years, Xu et al. proposed in [11, 12] an algorithm more accurate and robust to blood vessel occlusion, because the contour deforms to the location with minimum energy, and then the points of the contour are clustered into two groups, one group of the edge points and one group of uncertain points, which are finally updated by the combination of both local and global information (intensity distribution of each point along radial line in some range of pixels). The initial contour points are selected from the points of the best fitting circle of the optic disc. This circle is obtain applying circular Hough transformation on the edge map of the optic disc image. The disk center is set to be the initial origin of the contour deformation.

1.2. Data sets and materials

The database we use is one public database used also by Park et al. [8], the DRIVE database (Digital Retinal Images for Vessel Extraction). The photographs for the DRIVE database were obtained from a diabetic retinopathy screening program in The Netherlands. Each image has been JPG compressed. The images were acquired using a Canon CR5 non-mydiatic 3CCD camera with a 45 degree field of view (FOV). Each image was captured using 8 bits per color plane at 768 by 584 pixels. The FOV of each image is circular with a diameter of approximately 540 pixels. For this database, the images have been cropped around the FOV. For each image, a mask image is provided that delineates the FOV. The data set includes 40 584x565 fundus images. Even if the database is divided into a training set consisting of 20 images and a test set consisting of 20 images, we don’t use images for training our system, as other systems were doing. We use all 40 images for testing our methodology. All images are available for download at http://www.isi.uu.nl/Research/ Databases/DRIVE/download.php (the web site of Image Sciences Institute).

2. Methodology

The optic disc in the color retinal images appear as a bright region. The appearance of the optic disc is characterized by a rapid variation in intensity of adjacent pixels. The variance was used in our algorithm for the recognition of the optic disc.

A color fundus image have a dark background. The proposed methodology does not consider the background pixels. A mask image is computed with zero values for background pixels and one for the foreground pixels.

The pixels with the maximum intensity within the green plane (the green plane has been used because it shows the optic disc with highest contrast) of the image were searched (except some cases the pixels having maximum intensity are situated inside the optic disc). The center of mass of this region was taken as our initial point. Starting from this initial point eight ‘directions’ are considered: one direction for each 45 degrees in counter-clockwise. In each direction three points of interest are chosen (the ones for which there
is a rapid variation in intensity with the adjacent pixel in that direction).

In this way 24 points of interest were extracted (three for any of the eight directions). To each point of interest, the euclidean distance was associated (the distance between the initial point and the point of interest). The mean of all these distances was computed. Those points of interest having a distance major than this mean were excluded for future validations (Figure 1).

For each circle we consider the grey level of the pixels inside the disk and on the circumference. For this region we compute some descriptors of texture based on the intensity histogram of the region, in order to describe better the circle and in order to choose the best circle that fits the OD.

Moreover, we compute the texture measures using the statistical moments as in [2]. The expression for the \( n \)th moment about the mean is given by \( \mu_n = \sum_{i=0}^{L-1} (z_i - m)^n p(z_i) \) where \( z_i \) is a random variable indicating the intensity of one pixel, \( p(z_i) \) is the histogram of the intensity levels in the region, \( L \) is the number of possible intensity levels, and \( m = \sum_{i=0}^{L-1} z_i p(z_i) \) is the mean intensity.

Using these measures of texture, the methodology reduces the set of remaining circles following the next steps:

- preserves only the circles having the uniformity smaller than the mean of the uniformities of all remaining circles. This is done because the region is not a smooth region, but it seems more a coarse region and the uniformity is maximally uniform in smooth region and decreases from there in other type of regions;

- from the remaining circles, only the circles having the entropy greater than the mean of the entropies of all remaining circles were preserved. This is done because the randomness of the region is big enough, is not in any case a small randomness like in the case of a smooth region;

- after the step described above, only the circles having the third moment greater than the mean of the third moments of all remaining circles were preserved. This is done because we look for a circle having a disk with many pixels with high intensity (as we look for the OD) and so the histogram of the intensity levels must be skewed to the right (about the mean).

- in the end are preserved only the circles having the smoothness greater than the mean of the smoothness of all remaining circles. This is done because this value is very big for regions with large excursion in the values of its intensity levels, as we expect to be our OD region (because is covered by vessels).

Following these steps, from hundreds of circles we keep only less than twenty. Each remained circle (pixels from the disk and the circumference) is mapped then using the bilinear filtering into the polar coordinates space. In Figure 2(a) and Figure 3(a) we can see two circles. Their mapping images (in polar coordinates) can be seen in Figure 2(b) and Figure 3(b) respectively.

In only one central strip (Figure 2(c)) and Figure 3(c)) of the mapping images we look for the maximum derivatives in the \( y \) direction (Figure 2(d) and Figure 3(d)).
If \( \rho \) is the radius of the circle that we mapped into the polar coordinates space, then the set of the points of maximum derivatives in the \( y \) direction will have \( 2\pi \rho \) (the integer number nearest to it) elements.

To the set of the points of maximum derivatives in the \( y \) direction we apply the linear least squares fitting technique (linear regression). We try to find the best fitting straight line passing through the set of points described above (in Figure 2(e) and in Figure 3(e) we can see the regression line that best fits the set of the maximum derivatives). In order to quantify the quality of the fitting to the original data we compute the correlation coefficient.

In order to compute the correlation coefficient of a set of \( n \) data points \( (x_i, y_i) \), we first consider the sum of squared values \( ss_{xx}, ss_{xy} \) and \( ss_{yy} \) about their respective means, 

\[
ss_{xx} = \sum_{i=1}^{n} x_i^2 - n\bar{x}^2, \quad ss_{yy} = \sum_{i=1}^{n} y_i^2 - n\bar{y}^2 \quad \text{and} \quad ss_{xy} = \sum_{i=1}^{n} x_i y_i - n\bar{x}\bar{y},
\]

where \( \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \) and \( \bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \).

Then, the correlation coefficient is

\[
r^2 = \frac{ss_{xy}}{ss_{xx} ss_{yy}}.
\]

The equation of the regression line that best fit the set of the points will be

\[
y = \frac{ns_{xy} - s_y s_x}{ns_{xx} - s_x^2} x + \frac{s_{xx} s_y - s_{xy} s_x}{ns_{xx} - s_x^2},
\]

where \( s_x = \sum_{i=1}^{n} x_i \) and \( s_y = \sum_{i=1}^{n} y_i \).

We expect to have a correlation coefficient big (close to 1) for the circle that best fits the OD (as the maximum derivatives in the \( y \) direction are expected to be at the OD boundary and are expected to be best fitted by the line \( y = \rho \)).

For example, for the image in Figure 2(a), the correlation coefficient for the circle that best fit the OD is 0.9888, meanwhile for example for a circle which doesn’t fit the OD is 0.9771 (Figure 2 and Figure 3).

The circle that best fits the OD is chosen as the circle with the maximum correlation coefficient associated.

Figure 4 depicts an outline of the flow of the methodology.

3. Experimental results

The validation of the methodology needs a ground truth, that was set manually by an ophthalmologist. He estimated the OD as a circle by selecting some pixels on the OD boundary using standard software.

Our methodology identified correctly the OD location at 95% accuracy. That means that our algorithm produced for the localization of the OD better accuracy than produced other approaches. For example a method in [3] achieved 89% success rate for the localization of the OD, testing their method to a different data set.

In order to evaluate if the circle obtained by our algorithm fits the OD as good as the ground truth we consider the ratio \( S = \frac{\text{Area}(GT \cap C)}{\text{Area}(GT \cup C)} \), where \( GT \) is the ground truth circle and \( C \) is the circle obtained by the methodology. We compute also the euclidean distance between the center of
the ground truth circle and the center of the detected circle (this distance is another important measure used in order to evaluate the performance).

A ratio \( S = 0 \) indicates an excellent result (E), \( 0.5 \leq S < 0 \) denotes a good (G) result which requires improvement and \( S < 0.5 \) a fair (F) result. We have two bad results (B) because of the wrong positioning of the initial point (the initial point was chosen as the center of mass of the pixels with the maximum intensity within the green plane of the image). In these bad quality images the initial point is not within the OD area and that’s why we have false detection of the OD.

The average distance between the centers of the two circles (ground truth and proposed circles) is mean(\( \delta \text{cen} \)) = 8,9893 pixels with a standard deviation of std(\( \delta \text{cen} \)) = 9,7923 pixels, which is acceptable compared to the average of 9,75 pixels and standard deviation of 16,14 pixels obtained in [1].

The radius of the ground truth circle on all images in our database is between 27,9487 and 54,9904 pixels. Because the radius of the circle which best fits the OD is so variable, we don’t use Hough transform in order to detect the best circle which fits the OD (we don’t want to establish a priori a fixed radius for this circle).

For the best circle which fits the OD, we consider successful a circle which has associated a ratio \( S = 0.5 \), hence our algorithm achieved a success rate of 70%.

In the table 1 we tabulate the success rate of our algorithm (for the identification of the best circle which fits the OD) on all 40 images of the database.

Figure 5 shows an excellent (Figure 5(a)), a good (Figure 5(b)) and a fair (Figure 5(c)) OD boundary detection (circle that best fits the OD). For each result we overlap the result obtained with our algorithm and the ground truth.

### Table 1. Success rate for the best circle which fits the OD

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<th>Image name</th>
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<td>0.244</td>
<td>0.5376</td>
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Table 1: Success rate for the best circle which fits the OD (See text for details). COLUMN 1: Image name. COLUMN 2: \( \delta \text{cen} \). COLUMN 3: \( \delta \text{cen} \) is the euclidean distance between the center of the ground truth circle and the center of the detected circle. COLUMN 4: \( \delta \text{cen} \) is the radius of the ground truth circle. COLUMN 5: \( \delta \text{cen} \) is the radius of the circle proposed by our algorithm. COLUMN 6: result is an attribute which indicates how successful was the identification of the circle that best fits the OD.

### 3.1. Computational Performance

An important advantage of the proposed methodology is its fast computational time. The CPU time needed to process one image (584 x 565 pixels in size) on an Intel Core2 Duo (2.00 GHz) running Windows Vista is about 1 minute, but the algorithm can be optimized. This processing time is acceptable compared with the PCA which is quite time consuming as we can see in [5]. The proposed algorithm is also as fast as the method proposed in [1], where kNN regression is used in order to find only the position in the image which is located in the center of the OD (an average time of 1 minute, 30 seconds for the vessel segmentation and 30 seconds for the analysis).
4. Conclusion

We have presented a new methodology to automatically locate the optic disc in a retinal image. The algorithm detects the circle which best fits the OD and provides for this circle a center point and a radius. An important characteristic of this methodology is the lack of training. All 40 images of our database are used for test. Even if the database includes also bad quality images, we keep these images in our database in order to prove that the proposed methodology is robust. Another important characteristic is that we don’t use Hough transform for detecting the best circle that fits the OD and this because we don’t want to fix a priori a range for the radius of the circle or to fix a threshold value on the number of pixels of the circle. When other algorithms are using Hough transform, an accumulator array is computed corresponding to each of the radii from a range a priori established. Moreover, the computational time is also an important characteristic of the proposed methodology.

We apply the algorithm on the 40 testing images and we achieve a 95% success rate for the localization of the OD which is a remarkable result with respect to past results. We achieve also a 70% success rate for the circle that is best fitting the OD. Previous works do not all report quantitative results, the methods are tested on a different database or the performance evaluation method is different, hence is hard to find results against which we can compare our performance.

The results presented in this paper may be further improved by refining the way we choose the initial point. This point is chosen as the center of mass of the pixels with the maximum intensity within the green plane. In some bad quality images this choice causes a false detection of the OD.

5. Acknowledgments

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References