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OPTIC DISC LOCALIZATION BASED ON FEATURE SORTING

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Localization of the optic disc (OD) is a necessary step in automatic diagnosis of ocular diseases in retinal images: diabetic retinopathy, glaucoma and so on. In this paper, we combine different features and classification schemes to increase the performance of OD detection and localization. To this end, we propose a simple image processing algorithm based on adaptive local texture analysis considering different features, such as those extracted from the co-occurrence matrix, the fractal dimension and blood density. The selection of features is made in the learning phase, taking into account their relevance and non-redundancy. Retina images are decomposed in patches using the sliding box method. The presence of regions with different intensities and noise requires preprocessing operations. For OD recognition, a method which combines a voting scheme with a sorting procedure is applied. In the experiments, 100 images from the publicly available STARE dataset were used.

Keywords: local image processing, texture analysis, feature selection, sliding box method, optic disc localization.

1. INTRODUCTION

In retinal image analysis, detection and localization of some reference regions like the optic disc and macula are of greatest interest for the diagnosis of ophthalmic diseases. The OD, having an approximately round form, is a bright region of the ocular fundus, interrupted by the outgoing blood vessels. There are some difficulties in OD detection caused, for example, by the fact that the bright lesions, like exudates, have the same color as OD, or the non uniformity of illumination. Many researchers studied a variety of automated methods to segment and quantify the OD from digital retinal images [1, 2–4, 6–10, 13–15]. To this end, the authors presented in [14] a method which eliminates the exudates. The algorithm had the following phases: determination of the OD size taking into account image resolution, OD localization by using a binary template and bright regions removal. This algorithm had good results in OD detection, if the OD pixels are not darker than the background. Zeljković *et al*. [15] applied a morphological closing operation to find the brightest and largest region in the retinal image, which, however, may lead to wrong results if the OD has a similar area with the exudates. A couple of works combined vascular and intensity information for OD localization [2,6]. Thus, Fuente-Arriaga *et al.* [2] presented a methodology for glaucoma detection based on observing blood vessel distribution within the OD. Similarly, Youssif *et al*. [13] proposed an algorithm for OD detection based on matching the expected directional pattern of the retinal blood vessels. To this end, the retinal images were processed using primary filters. For localization of the OD center, the template matching of histograms on each color was used in [1]. In [8], the authors proposed a methodology for OD detection and center localization based on the analysis of textural and fractal features in patches with dimensions of 128×128 (coarse localization) and 16×16 (fine localization) pixels, created by the sliding box method and, respectively, by the fixed box method. The algorithm gave good results in the case of images without large exudates. The authors in [4] combined blood vessel segmentation and texture analysis to improve OD detection, so that we can conclude that, by combining different features, like those extracted from the co-occurrence matrix, fractal type features and blood density on different color channels, the accuracy of OD localization can be improved.

In this paper we propose an approach for automated OD detection based on the sliding box method for patch generation. The detection and localization algorithm is based on sorting feature values in two steps: first, a set of four patches corresponding to the minimum value of order is retained; second, from these candidates, the patch with maximum density of the principal blood vessels is considered.

2. FEATURE SELECTION AND OD DETECTION

For OD detection, we decomposed the initial retinal image on sub-images (patches) using a sliding box algorithm [8]. Then, the patches were processed and interpreted with the aid of a set of selected features of textural type. In order to properly localize the OD, it is necessary to choose a box of minimum sizes, so that the OD can be completely included in it. For example, in the case of the STARE database [12], the selected size was of 128×128 pixels. From a set of 16 features (Haralick type [3], fractal type [11]), we chose the most efficient ones to separate the OD box from the rest of the retinal image. Efficiency was tested on different color channels (R, G, B, H, S and V), as well. In a learning phase [8], we experimentally established that the features yielding the best results for OD detection were the following: contrast (C_d) (1), mean intensity (Im) (2) and differential fractal dimension (FD) (3) on the green channel. In these formulas, $M \times M$ represents the co-occurrence matrix dimension and $N \times N$ is patch dimension. C_d (1) is evaluated from a mean co-occurrence matrix – N_d on the eight main directions [8]. FD is calculated from (4), where $p(u,v)$ is the maximum value and $q(u,v)$ is the minimum value of green intensity in a box of size r placed in position (u,v).

$$C_d = \sum_{i=1}^{M} \sum_{j=1}^{M} (i-j)^2 N_d(i,j) \tag{1}$$

$$Im = \frac{1}{N \times N} \sum_{i=1}^{N} \sum_{j=1}^{N} I(i,j) \tag{2}$$

$$FD(r) = \frac{\log(\sum_u \sum_v n_r(u,v))}{\log r} \tag{3}$$

$$n_r(u,v) = p(u,v) - q(u,v) + 1 \tag{4}$$

The experimental results show that the extreme values of these features are concentrated on OD and exudates. Thus, a voting procedure for OD detection was proposed in [7] and [6]. To separate OD from exudates regions, a new approach was necessary. This approach is related to blood vessel segmentation, because the higher density of important blood vessels is concentrated in the OD region [4]. Therefore, the method consists of two phases: the first establishes the OD candidates based on texture analysis and the second determined the OD from the candidates, by blood vessel density evaluation. So, in the first phase we considered that C_d and *Im* take maximum values and *FD* takes minimum values for a patch containing OD. For C_d and *Im*, the patches are sorted in descending order of the values and, for *FD*, in increasing order. Because both the OD and exudates are brightest regions, the two types might be confused. Then, an addition criterion (maximum density of the main blood vessels in the candidate boxes) is necessary to put into evidence the OD from possible patches containing exudates. In this case, we chose the H component, which attenuates the intensity variation of the image. Some preprocessing techniques are necessary to segment the blood vessels: the adaptive histogram equalization technique by limiting contrast, morphological closing (5) and opening (6) with a structural element [4].

$$A \bullet B = (A \oplus B) \Theta B^S \tag{5}$$

$$A \bullet B = [A \Theta B(l,d)] \oplus B(l,d)^S \tag{6}$$

In the above equations, *A* represents the image, *B* is the structural element for closing and B^S is the mirrored structural element. The morphological opening operation is performed with the aid of a structural element with different directions $B(l,d)$.

The morphological opening operation is accomplished with the aid of different directional structural elements in the form of a line with a length of 50 pixels. The increment angle between directions is 15° over the interval [0°, 165°]. As a consequence of the binarization operation, the blood vessels are represented by white pixels (Fig. 1), and the rest of retinal image with black pixels. The density of these white pixels is the final criteria of OD detection. Patch position represents the OD localization in retinal image.

The proposed algorithm for OD detection and localization is the following:

Input: retinal images;
Output: box with the maximum density of white pixels (OD box and position);
1. Set the dimension of the boxes and the step of displacement;
2. Image decomposition on G and H color channels;
3. Noise rejection by median filter on G and H color channels;
4. Apply the sliding box algorithm on G and H color channels;
5. Compute *C*, *FD* and *Im* for each patch;
6. Select the first 10 patches with the largest *C* and *Im* and the smallest *FD*;
7. Extract the H component for each patch;
8. Apply the adaptive histogram equalization technique by limiting contrast on the H color channel;
9. Apply closing on the H color channel;
10. Substract the closing image from the adaptive histogram equalization technique by limiting the contrast image;
11. Apply the opening operation;
12. Image binarization using the threshold equal to 1;
13. Calculate the number of white pixels and retain the box (and its position) with the maximum number of white pixels.

3. EXPERIMENTAL RESULTS

To validate the proposed algorithm for OD detection, we used retinal images from STARE database [12]. The OD detection and localization work contains 100 images with 700×605 pixels, 24 bits. Figure 1 presents four test images (im0052, im0053, im0148 and im0223) and the obtained results (patches with OD and exudates and blood vessel segmentation). It can be seen that the OD patches have a high density of white pixels (corresponding to blood vessels), as also observed from Table 1. The resulting grid of patches has dimensions of 48×56, corresponding to the image and patch dimensions for the sliding box algorithm. The distance between two successive patches of 10 pixels was considered. Image processing was done with Matlab and FracLac software tools [5].

Table 2 lists the experimental results corresponding to images im0052 and im0148 for the first four positions, in ascending order for *FD* and in descending order for *C* and *Im*. For the second phase, the results of candidate selection for the final OD position are shown in Table 3. The patches with OD are considered those with the minimum sum of orders (a penalty of 10 points is considered if a patch is not in the first four positions). The decision is taken for the patch (from the set of candidates) which contains the maximum number of white pixels (maximum density of the main blood vessels).

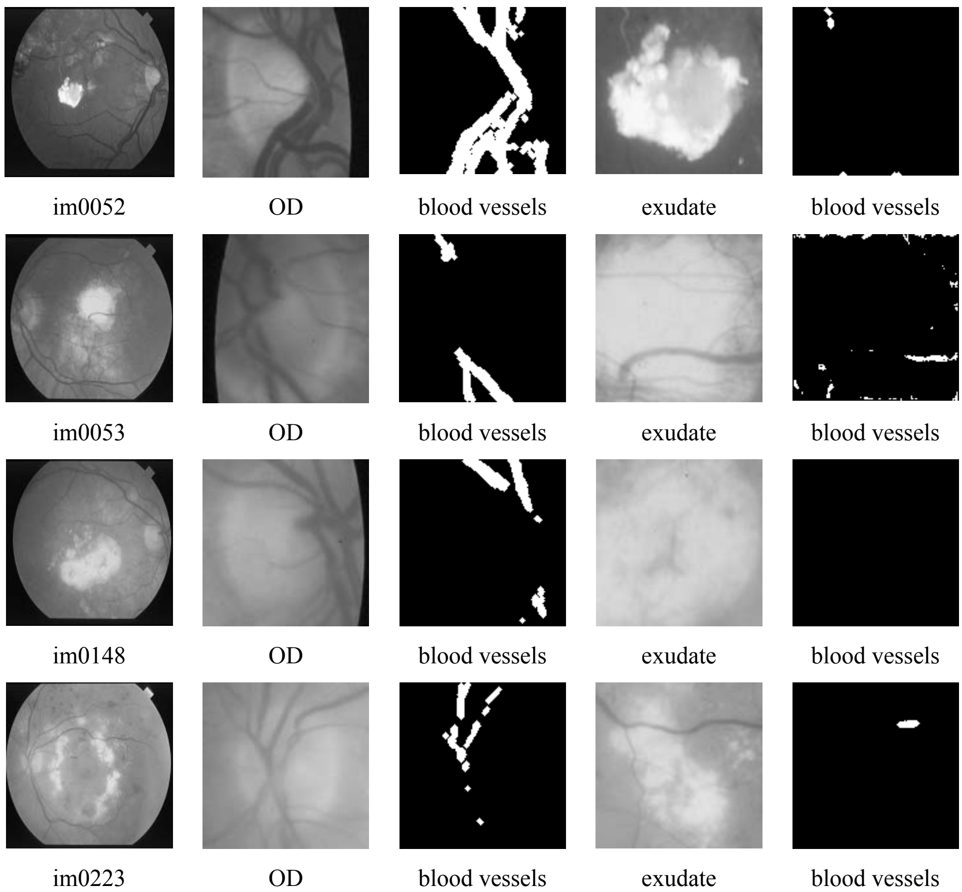

Fig. 1. Results of the proposed algorithm for four test retinal images.

Table 1

Density of pixels as a consequence of blood vessel segmentation on candidate patches

Patch	Density of pixels
im0052_DO_region	0.22
im0053_DO_ region	0.11
im0148_DO_ region	0.60
im0223_DO_ region	0.04
im0052_exudate_ region	0.01
im0053_ exudate _ region	0.05
im0148_ exudate _ region	0
im0223_ exudate _ region	0.01

Table 2

Experimental results related to the position criterion of patches for OD detection

Image	No.	Contrast (C)	Position C - criterion	Fractal Dimension (FD)	Position FD - criterion	Mean Intensity (Im)	Position Im - criterion
im0052	1	0.549	18_54	2.453	17_53	0.458	22_19
	2	0.533	20_18	2.456	18_54	0.432	18_54
	3	0.437	22_19	2.461	22_19	0.421	19_54
	4	0.315	19_54	2.472	20_18	0.407	20_18
im0148	1	0.556	27_25	2.462	26_20	0.506	27_25
	2	0.471	19_54	2.471	27_25	0.484	26_20
	3	0.401	25_21	2.477	19_54	0.478	27_24
	4	0.328	27_37	2.499	25_21	0.469	19_54

According to our algorithm, the positions of ODs are marked in Table 3. As stated above, our methodology was tested on 100 images from the STARE database, four of them having a wrong detection of OD. The accuracy of OD detection was 96%, compared with 91.36% in [1] and 95.75 % in [7].

Table 3

Experimental results combining the texture order and density of white pixels

Image	Patch position	Order	Density of white pixels	OD position
im0052	18_54	5	**0.22**	**DO: 18_54**
	22_19	7	0.1	
	20_18	10	0	
	19_54	17	0.1	
im0148	27_25	4	0	**DO: 19_54**
	19_54	9	**0.60**	
	26_20	13	0.01	
	25_21	17	0.01	

Experimental simulation was done on a PC with processor Intel Pentium Dual CPU E2200, 2.20 GHz and 3 GB of RAM, and the running time for OD detection was 12.3 s.

4. CONCLUSIONS

The objective of this paper was an accurate localization of the OD in retinal images. We considered a simple and efficient method, combining fractal and statistical features, on one hand, with blood vessels analysis, on the other. To obtain a high resolution, an ordering scheme for the selected features was adopted. The results indicate an OD detection accuracy of 96% from 100 test images.

Authors' contributions: Loretta Ichim and Dan Popescu had equal contributions in the paper.

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