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Detection of the optic disc in fundus images by combining probability models

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ABSTRACT

In this paper, we propose a combination method for the automatic detection of the optic disc (OD) in fundus images based on ensembles of individual algorithms. We have studied and adapted some of the state-of-the-art OD detectors and finally organized them into a complex framework in order to maximize the accuracy of the localization of the OD. The detection of the OD can be considered as a single-object detection problem. This object can be localized with high accuracy by several algorithms extracting single candidates for the center of the OD and the final location can be defined using a single majority voting rule. To include more information to support the final decision, we can use member algorithms providing more candidates which can be ranked based on the confidence ordered by the algorithms. In this case, a spatial weighted graph is defined where the candidates are considered as its nodes, and the final OD position is determined in terms of finding a maximum-weighted clique. Now, we examine how to apply in our ensemble-based framework all the accessible information supplied by the member algorithms by making them return confidence values for each image pixel. These confidence values inform us about the probability that a given pixel is the center point of the object. We apply axiomatic and Bayesian approaches, as in the case of aggregation of judgments of experts in decision and risk analysis, to combine these confidence values. According to our experimental study, the accuracy of the localization of OD increases further. Besides single localization, this approach can be adapted for the precise detection of the boundary of the OD. Comparative experimental results are also given for several publicly available datasets.

1. Introduction

More than 360 million people were suffering from diabetes in 2012 worldwide. The number of the diagnosed cases has been growing rapidly in the last few years and this tendency is estimated to continue [1]. Long-term diabetes also affects the eye, resulting in a disease called diabetic retinopathy (DR). If DR remains undiagnosed or is treated inappropriately, it can lead to the loss of vision. In addition, DR is the most common cause of blindness in the world. However, there are suitable ways of treatment to slow down the deterioration of the eye-sight. An automatic screening system for DR would be of great importance mainly in the developing countries, where nearly 40% of the cases remain undiagnosed. Such a system is useful if it is capable of detecting the first signs of the disease. The blood vessels that provide nourishment to the retina, in case of a person with diabetes, may weaken and leak, forming small, dot-like hemorrhages known as microaneurysms and hemorrhages. Exudates come into when fluid exudes from tissue because of its injured capillaries. The masking out the OD region in the image is highly recommended by [2–4] before the detection of exudates and cotton-wool spots, as these lesions appear in the retinal images as bright patches which are similar to the OD concerning their color and shape characteristics. Moreover, if the position and the radius of the OD are detected correctly, they can be used as references for approximating other anatomical parts e.g. the macula and the fovea, as it is proposed in [5] or to analyze pathologies e.g. glaucoma or neovascularization on the disc.

In the corresponding literature, several OD detection algorithms are published [6–15]. Most of these try to perform the extraction of the OD based on color, size, shape, direction of vessels, etc. For example, Mendels et al. [10] used morphological filtering and active contours to find the boundary of the OD, while Sekhar et al. [7] applied morphological operations and Hough-transformation to localize it. Here, the proposed method consists of two steps: in the first step, a circular region of interest is found by isolating the brightest area in the image by means of morphological processing, and in the second step, the Hough-transformation is used to detect the main circular feature (corresponding to the OD) in the positive horizontal gradient image within this region of interest. Abramoff et al. [8] proposed a kNN

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regression approach to find relationship between the dependent variable d which represents the distance from the OD center, and a feature vector extracted around a circular template. Shijian [9] used circular transformation which is capable of detecting both the OD center and its boundary from images of pathological retinas, as well. Lalonde et al. [10] proposed an algorithm (OD_{decomp}) which generates a pyramid with a simple Haar-based discrete wavelet transformation. The input image has low resolution after its decomposition is repeated four or five times and the pixel of this low-resolution image with highest intensity value is considered as the center of the OD. Another approach (OD_{edge}) in [10] uses edge detection applying the Rayleigh-based CFAR threshold. This solution guarantees the strong edges which are associated with the border of anatomical structures. In the next step, the Hausdorff distance is calculated between the set of edge points and a circular template like the average OD. The lowest distance value corresponds to the center of the OD. Sopharak et al. [11] proposed a method ($OD_{entropy}$) which applies a median and a CLAHE filter on the green intensity channel. The entropy of the intensity values in the local region around each pixel is calculated and the location of the highest entropy values is considered to belong to the OD. Niemeijer et al. [12] proposed feature extraction and classification steps ($OD_{classify}$) to determine the area of the OD. They suggest the following features: number, width, orientation and density of vessel segments. In the next step, a kNN classifier made a decision about each pixel whether they belong to the OD, or not. Hoover et al. [13] thinned the vessel system and each line-shape segment is modeled by a fuzzy segment. This model (OD_{fuzzy}) creates a voting map and the pixel obtaining the most votes is considered to be the center of the OD. Ravishankar et al. [14] proposed an algorithm (OD_{hough}) which uses Hough-transformation on the thinned vessel system. Lines which have slope less than 45° are eliminated. The intersection points of the rest of the lines give a voting map. Number of votes is weighted with the original intensity values of the intersection points in the image, and the highest corresponding value indicates the center of the OD. Finally, Zhu et al. [15] locate the border of the OD in terms of a circle with a given diameter using the circular Hough-transformation (OD_{cHough}). For this aim, edge detection is applied and the circle containing the most edge points is selected.

There is, in fact, no reason to assume that any single algorithm would be optimal for the detection of various anatomical parts of the retina. It is difficult to determine which the best approach is, because good results were reported for healthy retinas but weaker ones for more challenging datasets containing diseased retinas with variable appearance of ODs in term of intensity, color, contour definition and so on. To overcome the imperfectness of the individual algorithms, we study and adapt some of the state-of-the-art OD detectors and finally organize them into an ensemble framework in order to combine their strengths and maximize the accuracy of the localization of the OD. First in [16], we suggested an ensemble of them and tested a majority voting scheme with a circular template to detect the correct position of the OD center, where the individual algorithms had just a single candidate. As a further improvement of this model, in [17], we extracted more than one candidate for each algorithm to increase the chance of getting the OD location among them. We assigned weight to each candidate to replace simple majority voting by a weighted one and treated them as weighted nodes of a complete graph. For the location of the OD center, we selected that subgraph of the candidates which met the OD geometry constraint and had a maximal total weight. For this selection, we borrowed a graph theoretical approach supplying the optimal solution in terms of a maximal weighted clique.

Besides increasing the accuracy of the detection of the OD center, our aim is also the segmentation of the OD region so that it can be entirely eliminated before the detection of bright lesions. In this paper, we propose a method to maximize the accuracy of the localization of the OD and to determine its region. As we have mentioned earlier, in our former ensemble-based approaches we considered only one, then up to five possible OD center points as the output of each individual algorithm. Now, to utilize all available information corresponding to the possible location of the OD provided by the algorithms, we let them assign probability (confidence) values to each pixel of the input image. In this way, probability maps are composed of the member algorithms and a suitable combination of these maps can be considered to locate the correct OD region. Taking advantage of more information is supposed to lead to improvement, which is a natural expectation validated by our experiment studies. Namely, in our tests, the proposed method outperformed both the simpler ensemble-based systems and the state-of-the-art individual member algorithms on publicly available datasets.

The rest of the paper is organized as follows. In Section 2, we give a brief overview about our former ensemble-based systems used for OD detection. In Section 3, we introduce our methodology for the detection of the center and region of the OD based on the combination of probability maps provided by the individual algorithms. In Section 4, we describe the considered datasets for experimental evaluation. Section 5 is dedicated to our experimental results also in comparison with some other state-of-the-art OD detection methods. Finally, further technical details are discussed in Section 6, and some conclusions are drawn in Section 7.

2. Fusion of candidates for the OD center

In this section, we introduce our fusion strategies which are based on the majority voting scheme, finding maximal-weighted clique and combining probability maps, respectively. Besides giving detailed description of these frameworks, we show the positive effect of exploiting more and more information for the localization of a single object.

2.1. One member algorithm—One candidate

In [16], we have proposed an ensemble-based single object detection system based on simple majority voting which outperforms the member detectors [10–15]. Here, the single outputs for the object center of the member algorithms are merged and the majority voting scheme is applied using a template of the shape of the object to detect its correct position. More precisely, to overcome the imperfectness of the member algorithms, a template D is fit on each pixel $p_{x,y}$ of the input image I and the outputs of the algorithms that fall within D are summed. The center of the D covering the maximum number of detector outputs is considered to be a hot spot for the object. There can be more hot spots, hence they together define a hot spot region. To find the final center of the single object (x_{res}, y_{res}), the centroids of the outputs within the hot spot region are computed.

For an impression, see Fig. 1 for the output of the OD detectors OD_{decomp}, OD_{edge}, $OD_{entropy}$, $OD_{classify}$, OD_{fuzzy}, OD_{hough}, OD_{cHough} together with the manually selected center (ground-truth) OD_{manual} of the OD. As for the specific example in Fig. 1, with ignoring the candidates of OD_{edge} and OD_{fuzzy}, the true OD location has been found based on the ensemble of the result of OD_{decomp}, $OD_{entropy}$, $OD_{classify}$, OD_{hough} and OD_{cHough}.

To use the simple majority voting scheme for OD detection, a circular template D_R of radius $R>0$ is fit on each pixel and the outputs of the detectors within D_R are counted. Based on some preliminary experiments on the manually segmented OD regions (ODR), the value of R is set to 6.5% of the width of the region of interest (ROI) of the fundus image. In Fig. 2(a) and (b), we can