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A robust algorithm for optic disc segmentation and fovea detection in retinal fundus images

Abstract: Accurate optic disc (OD) segmentation and fovea detection in retinal fundus images are crucial for diagnosis in ophthalmology. We propose a robust and broadly applicable algorithm for automated, robust, reliable and consistent fovea detection based on OD segmentation. The OD segmentation is performed with morphological operations and Fuzzy C Means Clustering combined with iterative thresholding on a foreground segmentation. The fovea detection is based on a vessel segmentation via morphological operations and uses the resulting OD segmentation to determine multiple regions of interest. The fovea is determined from the largest, vessel-free candidate region. We have tested the novel method on a total of 190 images from three publicly available databases DRIONS, Drive and HRF. Compared to results of two human experts for DRIONS database, our OD segmentation yielded a dice coefficient of 0.83. Note that missing ground truth and expert variability is an issue. The new scheme achieved an overall success rate of 99.44% for OD detection and an overall success rate of 96.25% for fovea detection, which is superior to state-of-the-art approaches.

Keywords: optic disc segmentation, fovea detection.

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1 Introduction

Many important eye diseases manifest themselves in the retina. Retinal fundus images (cf. Figure 1) are thus a valuable and essential tool in ophthalmology. They allow detecting abnormalities and changes in the retina that indicate possible diseases. Particularly, the optic disc (OD) and the fovea are structures of clinical interest. Segmentation of these structures is therefore very important, but generally difficult as the images vary due to acquisition, poses, and medical conditions.

A first step is OD segmentation. The OD is the head of the optic nerve as it enters the retina coming from the brain. Typically, the OD appears as an area with high intensities in a fundus image and detection is thus relatively easy. However, the area is partly covered by dark blood vessels that represent a strong contrast and complicate the OD segmentation. Therefore, preprocessing steps for a blood vessel removal are necessary [1]. Devasia et al. [1] propose to combine morphological operations and Fuzzy C Means Clustering with thresholding. Our novel scheme uses threshold segmentation steps during preprocessing and an iterative thresholding for the Fuzzy C Means Clustering.

The second step is the fovea detection. An accurate OD segmentation can be exploited for the detection and segmentation of the fovea. The fovea is a pit in the retina that is responsible for sharp vision. In fundus images it appears as an area with low intensities that is free of blood vessels. The automatic detection is difficult, but at the same time important as changes in the appearance of the fovea indicate possible diseases. Therefore, a robust, reliable and consistent fovea detection is crucial. Following Samanta et al. [2], the fovea is typically located in a 5 times radius of the OD from its centre [2]. Thus, OD segmentation can readily be used for fovea detection. Our new approach for the fovea detection is an adaption of the method in [2]. In addition to the vessel segmentation via morphological operations and search for the fovea at a 5 times radius distance, we expand the search to locations at several distances. Moreover, we constrain the search area through information obtained from our preprocessing steps.

2 Materials and methods

All images used in this paper are obtained from the DRIONS database [3], Drive database [4], and HRF database [5]. The DRIONS database contains 110 retinal colour images of size 400 × 600 pixels showing only the OD which is located at the image centre. It also provides two corresponding expert reference segmentations of the OD for each image. The Drive database contains 40 colour images of size 565 × 584 pixels of which 35 of those images show the OD and the fovea, and 5 images only show the OD. The HRF database contains 45 colour images of size 3504 × 2336 pixels, subdivided into 15 images of healthy patients, patients with diabetic retinopathy, and glaucomatous patients respectively. All 45 images show the OD and the fovea. The images are centred on the fovea.

The proposed algorithm is organized in two steps. First we find a segmentation for the OD and then use the result for the detection of the fovea

2.1 Optic disc segmentation

For the segmentation of the OD we follow the approach of Devasia et al. [1]. They propose to first separate the red channel of the colour image, then remove the blood vessels with mathematical morphological operations and subsequently use Fuzzy C Means Clustering combined with thresholding for the segmentation of the OD as a bright object. In anticipation of the following fovea detection we use a grey-scale image computed from the RGB-values by Craig's formula (see eq 1), as proposed by Samanta et al. [2]. For better results, we additionally use Otsu's method [6] for a foreground-background separation of the image in order to constrain the region of interest for the OD segmentation. Furthermore, we introduce an iterative thresholding process for the Fuzzy C Means Clustering.

2.1.1 Preprocessing

During preprocessing of the images, we use Craig's formula to calculate the grey-scale image. The local grey value (GV) is determined from red (R), green (G) and blue (B) colour channels of the RGB images:

$$\boldsymbol{GV = 0.3 \cdot R + 0.59 \cdot G + 0.11 \cdot B} \qquad (1)$$

Afterwards, we apply a median filter for noise reduction. Otsu's method is then used to find the image's foreground, which represents the area of the eye within the image. In order to identify the bright regions within the area of the eye R_B Otsu's method is applied again solely on the previously determined foreground. For the following fovea detection, a mask of the dark regions within the area of the eye R_D is created by combining the first found background with the second found foreground.

2.1.2 Blood vessel removal

Blood vessels appear as dark structures in the grey-scale images and cross the OD. Therefore, they make the segmentation of the OD as a bright object difficult and have to be removed beforehand. Unsharp masking using dilatation with a 10 × 10 disc structuring element and subsequent closing with a 10 × 10 disc structuring element removes the blood vessels and smoothes the resulting image.

2.1.3 Fuzzy C means clustering with iterative thresholding

After removal of the blood vessels, we use the MATLAB Fuzzy C Means Clustering function *fcm* with three clusters on the region of interest R_B. An iterative thresholding is applied to the points of the brightest of the three clusters. The threshold τ is defined as

$$\boldsymbol{\tau = \mu \cdot (GV_{max} + GV_{min})} \qquad (2)$$

where GV_{max} and GV_{min} are the maximum and minimum grey value of the points of the brightest cluster. The factor μ is initialized as μ = 0.5 and iteratively raised if the ratio

$$\boldsymbol{r} = \frac{\#\text{ pixels with } \boldsymbol{GV>\tau}}{\#\text{ image pixels}} \qquad (3)$$

is greater than 1/25. After finding the optimal threshold, we choose the biggest connected component and obtain our final OD segmentation by filling enclosed holes.

2.1.4 Boundary extraction

The exterior boundary of the OD segmentation is traced and Kasa's method [7] is used to find an algebraic circle fit for the segmented OD. This provides an approximation of the

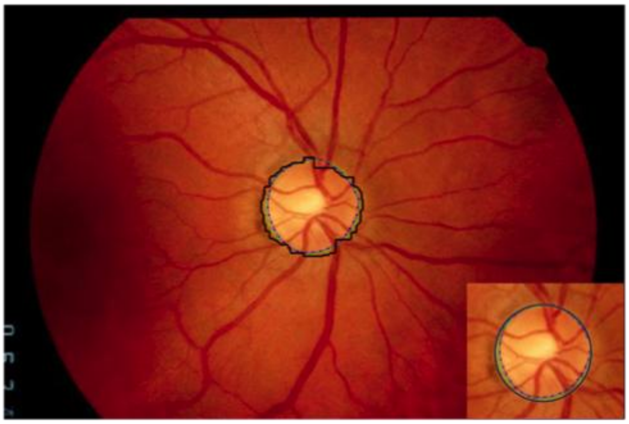

Figure 1: Segmentation of the OD. The green and blue lines are two expert segmentations of the OD. The black line shows the segmented OD. In the smaller picture, the black line shows the circle fit by Kasa's method.

centre c_{OD} and the radius r_{OD} of the segmented OD that is needed for the fovea detection.

2.2 Fovea detection

For the detection of the fovea we follow the approach of Samanta et al. [2]. They propose to first segment the blood vessels with mathematical morphological operations and then find the fovea as the darkest object between the segmented vessels at a $(5 \cdot r_{OD})$-distance from c_{OD}. In our approach, we expanded the search area for the fovea by computing and comparing search results for four different distances from c_{OD}. At the same time we use prior knowledge of R_D and the assumption that the fovea lies approximately on the same horizontal line as the OD to constrain our search area.

2.2.1 Preprocessing

Our experiments indicate that the algorithm for the OD segmentation tends to segment a rather small OD area even when using the blood vessel removal. This is due to the strong presence of blood vessels on the half of the OD opposite to the fovea. We compensate for this phenomenon by shifting the centre c_{OD} on a horizontal line away from the image centre and enlarging the radius by factor 5/3.

2.2.2 Vessel segmentation

Following [2], we perform a vessel segmentation on the grey-scale image using first an opening with a 7 × 7 disc structuring element and then a closing with a 17 × 17 disc structuring element. The difference image of the closed and the original grey-scale image is used to create a binary image by applying a threshold of zero. After deleting areas that are proportionally smaller than a predefined ratio, we obtain a vessel segmentation that is sufficient enough for further proceedings. In contrast to [2], we then add the binary information of the vessel segmentation to the mask R_D.

2.2.3 Determine region of interest

For determining the region of interest (ROI) we define four points of interest (POI) horizontally at distances $d_i \cdot r_{OD}$, $d = [3.4, 4, 4.6, 4.8]$ from c_{OD}. The previous enlargement of r_{OD} causes smaller factors d_i than proposed by Samanta et al. [2]. For each POI, we then define a ROI(POI) as the $(9 \times 6 \cdot r_{OD})$-window around POI in $\overline{R_D} := 1 - R_D$. Afterwards, we compute the maximum number of white pixels within the binary windows λ^* and save the corresponding $\overline{\mathrm{POI}}$, where

$$\boldsymbol{\lambda}^* = \mathbf{max}_{\mathrm{POI}}\{\#\ \mathbf{1} \text{ in ROI(POI)}\} \tag{1}$$

$$\overline{\mathbf{POI}} = \mathbf{arg\ max}_{\mathrm{POI}}\{\#\ \mathbf{1} \text{ in ROI(POI)}\}, \tag{2}$$

and perform a case analysis if $\lambda^* \notin [\lambda_{min}, \lambda_{max}]$ for predefined λ_{min}, λ_{max}. If $\lambda^* > \lambda_{max}$, $\overline{\mathrm{POI}}$ is shifted towards $\underline{\mathrm{POI}} = \arg\min_{\mathrm{POI}}\{\#\ 1 \text{ in ROI(POI)}\}$. If $\lambda^* < \lambda_{min}$, d is extended to include values [3.2, 3.7, 4.3, 4.7, 5.4] and computations for λ^*, $\overline{\mathrm{POI}}$ are repeated. The largest connected component L of ROI($\overline{\mathrm{POI}}$) is computed as well as its centre c_L and its vertical radius r_L.

2.2.4 Fovea detection

Dilatation of a single point in position c_L with a $r_L \times r_L$ disc structuring element yields a mask R_F for the fovea region. A

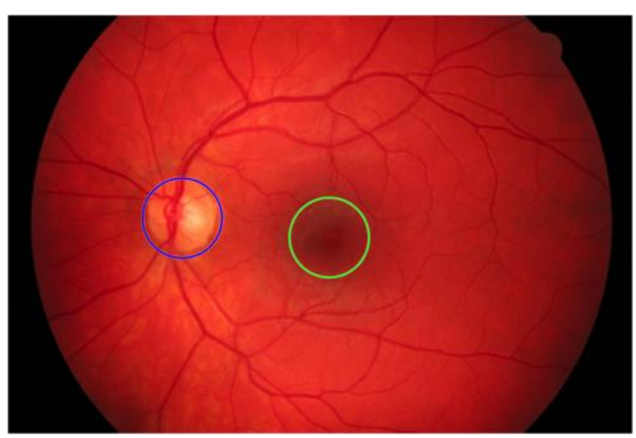

Figure 2: The blue circle shows the segmented OD. The green circle shows the determined fovea region.

mask for the fovea detection is created by combining $\overline{R_D}$ with R_F.

We then apply Otsu's method to the original grey-scale image within the new mask and find a fovea region as the largest connected component in the background. The exterior boundary of the fovea region is traced after enclosed holes are filled and Kasa's method is used to find an algebraic circle fit for the segmented fovea region. This yields the centre c_{fovea} and the radius $r_{fovea} = \max\{r_{fovea}, r_{OD}\}$ of the segmented fovea region that includes the fovea.

3 Results

Exemplary results of OD segmentation and fovea detection in a fundus image are shown in Figure 1 and 2. To demonstrate robustness, reliability and broad applicability, the proposed approach was tested on 190 images from three publicly available databases: DRIONS, Drive and HRF database.

For the DRIONS database, that only shows the OD, OD segmentation was performed only. Considering that no fovea detection was performed, we forwent the grey-scaling of the image and used the red channel instead. The success rate of the OD detection for the 110 images was 100%. The Drive database consists of 35 images showing OD and fovea. Five images only show the OD and were excluded from testing. The proposed approach for fovea detection yielded a success rate of 100%. Finally, we tested the algorithm for fovea detection on the 45 images of the HRF database. Due to computation time we rescaled the images to the size 468 × 701. The success rate was 93.3%.

We additionally compared our OD segmentation results with two expert segmentations provided by the DRIONS database. The mean dice coefficient is 0.83. Note that missing ground truth and expert variability is an issue and was not evaluated.

4 Discussion

A novel approach for fundus image segmentation is proposed. The new scheme achieved an overall success rate of remarkably 99.44% for OD detection and an overall success rate of 96.25% for fovea detection, which is superior to state-of-the-art approaches. On the Drive database our algorithm outperformed the method proposed by Samanta et al. [2], which only achieved a success rate of 97.14%, whereas our method yielded a success rate of 100%. On the HRF database our algorithm achieved a 93.3% success rate producing only three false fovea detections even though the database consists mostly of abnormal images of diseased patients. Only one of them is the result of an incorrect OD segmentation. This demonstrates that the proposed OD segmentation approach performs reliable and consistent on a wide variety of datasets.

The testing results on the three databases show that our proposed algorithm is robust and applicable to multiple databases and generally outperforms recent methods. Otsu's method is used in order to improve the performance of the Fuzzy C Means algorithm, which we combine with an iterative thresholding for wide applicability. We compensate for typical weaknesses in the OD segmentation by shifting and enlarging the OD segmentation results before starting the fovea detection. In addition to morphological operators and geometrical features, we use further prior information about the fovea region for the localization of the fovea. This allows us to compute and compare several possible fovea locations within an extended fovea search region. Thus, the proposed algorithm is robust and performs more successfully even in case of challenging retinal fundus image databases.

Author's Statement

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