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Optic Disc Detection by Earth Mover's Distance Template Matching

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***Abstract*—**This paper presents a method for the detection of OD in the retina which takes advantage of the powerful preprocessing techniques such as the contrast enhancement, Gabor wavelet transform for vessel segmentation, mathematical morphology and Earth Mover's distance (EMD) as the matching process. The OD detection algorithm is based on matching the expected directional pattern of the retinal blood vessels. Vessel segmentation method produces segmentations by classifying each image pixel as vessel or nonvessel, based on the pixel's feature vector. Feature vectors are composed of the pixel's intensity and 2D Gabor wavelet transform responses taken at multiple scales. A simple matched filter is proposed to roughly match the direction of the vessels at the OD vicinity using the EMD. The minimum distance provides an estimate of the OD center coordinates. The method's performance is evaluated on publicly available DRIVE and STARE databases. On the DRIVE database the OD center was detected correctly in all of the 40 images (100%) and on the STARE database the OD was detected correctly in 76 out of the 81 images, even in rather difficult pathological situations.

***Keywords*—**Diabetic retinopathy, Earth Mover's distance, Gabor wavelets, optic disc detection, retinal images

I. Introduction

THE retina is the inner-most and the important layer of the eye where the earliest pathological changes are seen. It is composed of various anatomical structures which indicate many diseases, such as hypertension, diabetic retinopathy and glaucoma. Retinopathy is one of the main causes of blindness in the working age population. Analysis of retinal images is considered essential for diagnosis and treatment of many diseases affecting the retina. These images must be accurately segmented to extract sensitive objects in the retina such as the blood vessel tree, the optic disc, the macula and the region between the optic disc (OD) and the macula.

Retinal or fundus images provide information about the blood supply system to the retina. The OD which in fundus images usually appears as a round region brighter than the surrounding is the image of the optic nerve and is the exit point of retinal nerve fibers from the eye and the entrance and exit point for retinal blood vessels. It consequently has a very different appearance to the rest of the retina, usually appearing as a bright, approximately circular region intersected by blood vessels (See Fig. 1(a)). Optic Disc detection is a reference to locate the various anatomical features in the retinal images and its location is quite important since many retinal pathologies may affect the optic nerve. Anatomical variation as well as refractive differences between eyes affect its apparent size. Since the OD may be easily confounded with large exudative lesions by image analysis techniques, its detection is also important to exclude it from the set of possible lesions. Although manual localization of the OD is sufficient, the process can be prohibitively cumbersome when dealing with large number of images. This has stimulated several research groups to develop algorithms for automatic localization of the OD [1].

OD localization methods can be classified into two main categories, appearance-based methods and vessel-based methods. Appearance-based methods identify the location of the OD as the location of the brightest round object within the retinal image. Lalonde et al. [2]) implemented a Hausdorff-based template matching technique using edge maps, guided by pyramidal decomposition for large-scale object tracking. Zhu et al. [3] proposed a method based on edge detection and the Hough transform for the detection of circles in areas where the highest local maximum in the Hough space also meets the condition based on 90% of the reference intensity. In Li and Chutatape [4], the brightest 1% of image pixels were firstly clustered as candidate optic disc regions. The regions larger than a fixed area threshold were taken as candidate regions for the optic disc. Next, principal component analysis based on a training set of ten manually extracted optic discs, normalized for size and intensity, was used to select a single point in the candidate regions. Then, the location of the optic disc center was found by calculating the minimum distance between the original retinal image and its projection. These techniques, however, often fail on pathological images, where atypical pigmentation, therapeutic laser scars and a number of pathological features may be characterized by round shape and/or elevated brightness, e.g., large exudative lesions.

Vessel-based methods depend mainly upon extracting and analyzing the structure of the retinal vessels and defining the location of the OD as the point where all the retinal vessels radiate. In Hoover and Goldbaum [5], an original vessel segments fuzzy convergence algorithm was proposed to identify the position of the optic nerve image as the focal point of the blood vessel network. The method of Foracchia et al. [6] is based on a model of vessel orientation in the retina relative to the optic disc position. The model was fitted to the measured vessel directions using simulated annealing, the measurements being weighted by vessel calibre so that larger vessels have a greater influence on the result. Relying on matching the expected directional pattern of the retinal blood vessels in the vicinity of the OD, Youssif et al. [7] proposed a method to

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detect the OD. A two-dimensional Gaussian matched filter was used to obtain a direction map of the segmented retinal vessels. The Gaussian matched filter was resized in four different sizes, and the difference between the output of the matched filter and the vessels' directions was measured. The minimum difference was used to estimate the coordinates of the center of the OD.

In this work, a technique for OD detection is proposed. The new method can be classified as a vessel-based method in which the OD is considered the region where the main retinal vessels originate in a parabolic direction. This method takes advantage of the powerful preprocessing techniques such as the contrast enhancement, Gabor wavelet transform, mathematical morphology and Earth Mover's distance for the matching pattern. The methods include the design of a bank of directionally sensitive Gabor filters for several values of the scale and elongation parameters as proposed by Soares et al. [8]. Forty images of the retina from the DRIVE database [9] and 81 images of the retina from the STARE database [5] were used to evaluate the performance of the method.

The rest of this paper is organized as follows. Section II describes the proposed OD detection technique. Experimental results are then described and discussed in Section III. Some concluding remarks are finally drawn in Section IV.

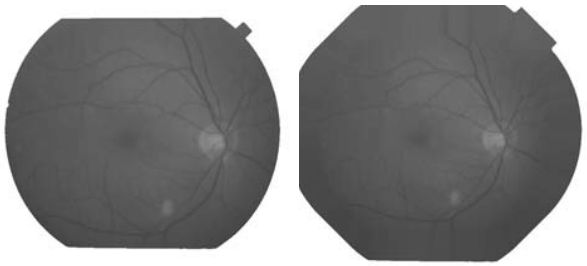
II. Proposed Method

This section presents the proposed OD detection technique. In particular, we divide this section into three subsections, which deal with the retinal image preprocessing, blood vessel segmentation, and OD detection, respectively.

A. Retinal Image Preprocessing

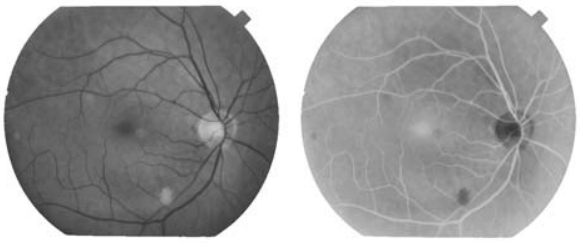
Retinal images need to be preprocessed before the OD detection. Several other works on the detection of retinal vessels have used the green channel only, however, as the proposed technique makes use of the brightness of the OD, the lightness component within the CIE-Lab colour space of a retinal image is first extracted (Fig. 1(a)). The CIE-Lab space allows us to work with just the luminance in an image without suffering from colour noise influence.

In order to reduce false detection of the border of the camera's aperture, an iterative algorithm has been developed. We used the method proposed by Soares et al. [8]. Our intent is to remove the strong contrast between the retinal fundus and the region outside the aperture. The preprocessing algorithm starts with a region of interest (ROI) determined by the camera's aperture and iteratively grows this ROI by replace each pixel value with the mean value of its eight neighbours inside the ROI. Finally, the ROI is expanded by inclusion of this altered set of pixels. This process is repeated and can be seen as artificially increasing the ROI, as shown in Fig. 1(b). Without some type of colour normalization for the background pigmentation, the large variation in natural retinal pigmentation across the population confounds discrimination of the relatively small variations between the different lesion types. As the contrast between the blood vessels (foreground) and the retinal tissue (background) is generally poor in the retinal images, an effective technique called contrast-limited



(a) (b)

Fig. 1 Fundus image extension for removing undesired border effects. **(a)** Lightness of STARE's retinal image in CIE-Lab colour space. **(b)** Image with extended border.



(a) (b)

Fig. 2 Retinal image preprocessing.**(a)** Result of contrast enhancement with CLAHE. **(b)** Inverted image were vessels appear brighter than the background

adaptive histogram equalization (CLAHE) is used for contrast enhancement by limiting the maximum slope in the transformation function. Instead of applying the histogram equalization on the entire image, it is applied only on small non-overlapping regions in the image. Then, the neighbouring tiles are combined using bilinear interpolation to reduce induced boundaries. Fig. 2(a) shows the contrast enhancement produced by CLAHE approach.

The contrast enhanced image is inverted before the application of the wavelet transform to it, so that the vessels appear brighter than the background as showed in Fig. 2(b).

B. Blood Vessel Segmentation

In many applications of image processing in ophthalmology, the most important step is to detect the blood vessels in the retina. Many algorithms have been developed for extracting the vascular structure from fundus images [5], [6], [8].

We propose image processing techniques to detect blood vessels in images of the retina based upon Gabor wavelet [8] which takes advantage of the fact that blood vessels are elongated, piecewise-linear or curvilinear structures with a preferred orientation. This approach produces segmentations by classifying each image pixel as vessel or nonvessel, based on the pixel's feature vector. Feature vectors are composed of the pixel's intensity and 2D Gabor wavelet transform responses taken at multiple scales.

Gabor wavelets are sinusoidally modulated Gaussian functions that have optimal localization in both the frequency and space domains, thus allowing noise filtering and vessel enhancement in a single step. The wavelet is capable of

detecting directional structures and of being tuned to specific frequencies, which is especially important for filtering out the background noise present in retinal images.

The notation and definitions in this section follow [8].

The continuous wavelet transform $T_\psi(\mathbf{b},\theta,a)$ is defined in terms of the scalar product of f with the transformed wavelet $\psi_{\mathbf{b},\theta,a}$. This transform can be easily implemented using the fast Fourier transform algorithm and the equivalent Fourier definition of the wavelet transform:

$$T_\psi(\mathbf{b},\theta,a) = C_\psi^{-1/2} a \int \exp(j\mathbf{kb})\hat{\psi}^*(ar_{-\theta}\mathbf{k})\hat{f}(\mathbf{k})d^2\mathbf{k} \quad (1)$$

where $C_\psi, \psi, \mathbf{b}, \theta, a$ denote the normalizing constant, analyzing wavelet, the translation vector, the rotation angle, and the dilation parameter (also known as scale), respectively. ψ^* denotes the complex conjugate of ψ and the hat (i.e., $\hat{\psi}^*$ and $\hat{f}$ denotes a Fourier transform. The Gabor wavelet is actually a complex exponential modulated Gaussian, where $\mathbf{k}$ is a vector that defines the frequency of the complex exponential.

For each pixel position and considered scale value, we are interested in the response with maximum modulus over all possible orientations, i.e.,

$$M_\psi(\mathbf{b},a) = \max_\theta \left| T_\psi(\mathbf{b},\theta,a) \right|. \quad (2)$$

The Gabor wavelet transform is computed for spanning from 0 up to 170 degrees at steps of 10 degrees. The maximum moduli of the wavelet transform over all angles for various scales are then taken as pixel features. The filter elongation parameter was set to $\varepsilon = 4$ and $\mathbf{k}_0 = [0,3]$.

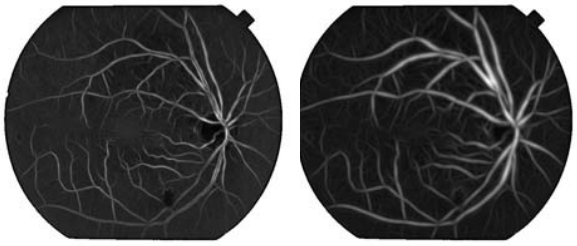
Fig. 3 shows the results obtained using scale values of $a = \{2,5\}$ pixels. The result in Fig. 3(a) indicates that the filters have detected only the edges of the thick vessels, with poor response along their center-lines. On the contrary, the result in Fig. 3(b) shows that, while the thick vessels have been detected well, some of the thinner vessels have not been detected. The results indicate the need for multiscale or multiresolution filtering and analysis, which is easily facilitated by the proposed design of the Gabor wavelet.

In the tests performed, the scale parameter is varied as $a = \{2,3,4,5\}$ pixels. These scales were chosen as to span the possible widths of vessels throughout the images, so that all vessels could be detected. Illustrative segmentation results for a pair of images from the STARE dataset, along with the manual segmentations, is shown in Fig. 4.

C. Optic Disc Detection

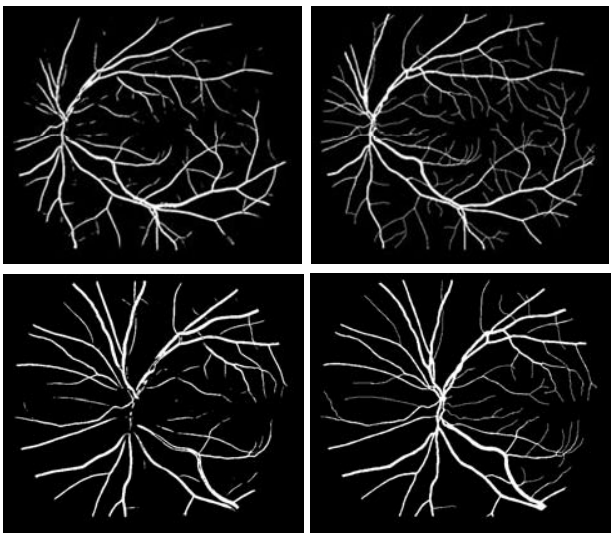
A distinguishing feature of the optic disc is that it is the region of convergence for the blood vessel network. The shape, colour, and size of the OD showed large variance especially in the presence of retinopathies, and therefore, detection methods based on these properties were shown to be weak, and impractical.

As stated by Hoover et al. [5], "A matched filter describes the expected appearance of a desired signal, for purposes of comparative modeling". Thus, in order to detect the OD, a simple vessel's matched filter is proposed to roughly match the vessels at the OD vicinity.



(a) (b)

Fig. 3. Maximum modulus response of Gabor wavelet transform over 18 Gabor filters with $\varepsilon = 4$ and $\mathbf{k}_0 = [0,3]$. **(a)** Scale value of $a = 2$ pixels. **(b)** Scale value of $a = 5$ pixels.



(a) (b)

Fig. 4 Blood vessel segmentation **(a)** Two images from STARE database. **(b)** Manual segmentations

By visual inspection of retinal fundus images, it appears that a common vascular pattern is present among images: the main vessels originate from the OD follow a specific course that can be geometrically modeled as two opposite semi-parabolas, with a common vertex inside the OD. The distance between the pattern and the thinned vessel map is obtained using the Earth Mover's distance (EMD) approach.

Rubner et al. [10] introduced the EMD to measure perceptual similarity between images for the purpose of image retrieval. EMD evaluates dissimilarity between two distributions or *signatures* in some feature space where a distance measure is given. Intuitively, given two distributions, one can be seen as a mass of earth properly spread in space, the other as a collection of holes. Then, the EMD measures the least amount of work needed to fill the holes with earth. Here, a unit of work corresponds to transporting a unit of earth by a unit of ground distance. The EMD between two distributions is given by the minimal sum of costs incurred to move all the individual points between the signatures.

Let $P=\{(p_1,w_{p_1}),...,(p_m,w_{p_m})\}$ be the first signature with m pixels, where p_i is the pixel representative and w_{p_i} is the weight of the pixel; the second signature with n pixels is represented by $Q=\{(q_1,w_{q_1}),...,(q_n,w_{q_n})\}$, and $D=[d_{ij}]$ the distance matrix where d_{ij} is the distance between two points' image coordinates p_i and q_j. The flow f_{ij} is the amount of weight moved from p_i to q_j. The EMD is defined as the work normalized by the total flow f_{ij}, that minimizes the overall cost:

$$EMD(P,Q)=\frac{\sum_i\sum_j f_{ij}d_{ij}}{\sum_i\sum_j f_{ij}} \quad (3)$$

As pointed by Rubner et al. [10], if two weighted point sets have unequal total weights, EMD is not a true metric. It is desirable for robust matching to allow point sets with varying total weights and cardinalities. In order to embed two sets of contour features with different total weights, we divide the blood vessel image in several overlapping tiles and simulate equal weights by adding the appropriate number of points, to the lower weight set, with a penalty of maximal distance. As a measure of distance for the EMD, we use

$$d_{ij}=1-e^{-\frac{\|p_i-q_j\|}{\alpha}} \quad (4)$$

where $\|p_i-q_j\|$ is the Euclidean distance between p_i and q_j and α is used in order to accept some deformation of the matching pattern. The exponential map limits the effect of large distances, which otherwise dominate the result.

To reduce the computational burden, pattern matching is applied only to candidate pixels picked from the fundus image [7]. The retinal image is smoothed using the bilateral filter [11] that combines geometric closeness and photometric similarity. Fig. 5(a) shows the filtered retinal image of Fig. 2.

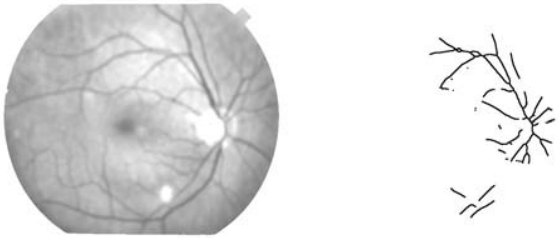
The binary vessel/nonvessel image is thinned by applying a morphologic algorithm that reduces all objects in the binary image to the pixel dimension keeping in the new image only the central pixels of the vessels. The number of candidates is reduced by considering only the ones which are within a 41×41 square centered on each of the highest 4% intensity pixels in the image as showed in Fig. 5(b).

III. Experimental Results

This section presents experimental results. The two public datasets used are first described. The performance of the proposed OD detection method is then presented and discussed.

A. Data Description

The proposed method was tested with fundus images of the retina from two public datasets. In particular, the first dataset is Digital Retinal Images for Vessel Extraction (DRIVE) database that is composed of 40 images (seven of which present pathology) obtained from a diabetic retinopathy screening program. The images are acquired using a Canon CR5 3CCD camera at 45º field of view, compressed in JPEG format of size 565×584 pixels, eight bits per colour channel and have a FOV of approximately 540 pixels in diameter. The 40 images were divided into two sets, a test set and a training set, each containing 20 images. The second one is Structured Analysis of the Retina (STARE) database, which consists of 81 images captured by a TopCon TRV-50 fundus camera at 35º FOV. The images were digitized to 700×605 pixels, eight bits per colour channel. The FOV in the images are approximately 600 pixels in diameter. The dataset is composed of 50 images containing pathological lesions of various types and severity and 31 images of healthy retina. It is created for benchmarking OD detection and is much more challenging compared with the DRIVE dataset.



(a) (b)

Fig. 5 OD center candidates. **(a)** Retinal image smoothed by bilateral filtering. **(b)** Final OD center candidates

B. OD detection results

As proposed also in [6],[7], the OD position was considered correctly detected if the estimated coordinates were inside the contour of the OD, i.e., within 60 pixels of its center, as manually identified for ground truth. The method was able to correctly detect the OD in 116 out of 121 images.

Fig. 6 shows some illustrative OD detection results. Examples of highly pathological images in which the OD was successfully identified are shown in the second row of Fig. 6.

C. Discussion

Although we do not show any images from DRIVE dataset, we have tested the proposed technique in that dataset with a success rate of 100% (the OD center was detected correctly in all of the 40 images).

Results on the 81 normal and pathological images of the STARE project were satisfying, despite the presence of heavily confounding features in many of them. For example, in the images shown in Fig. 6, middle, the retina covered by extensive retinal lesions, either dark hemorrhages or bright exudates, and would have proved impossible to be detected by techniques based only on brightness or shape. Thanks to the fusion information from retinal vessel geometry and brightness, the proposed technique was able to correctly identify the position of OD also in these very difficult images. In the images of Fig. 6, bottom, the proposed method fails due mainly to severe hemorrhages which make the blood vessels undefined and darken the OD pixels. Also, the method did not perform well for very large variations in lighting

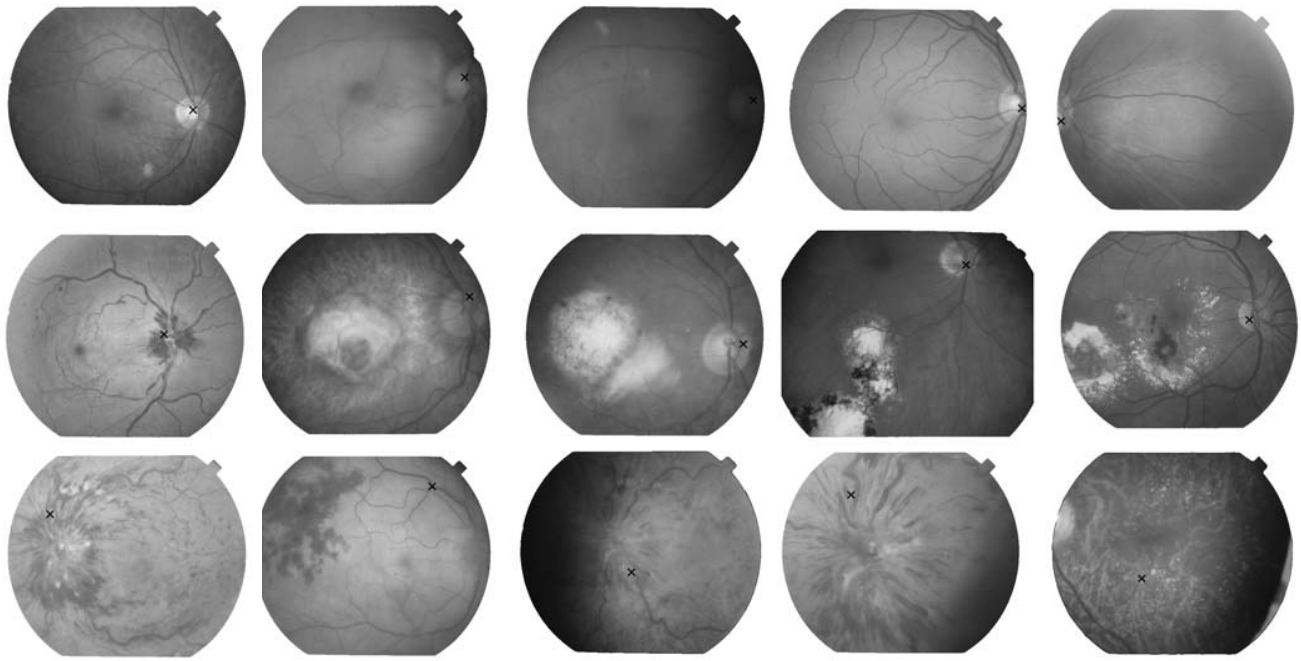


Fig. 6 OD detection examples within STARE dataset (black mark (x) represents the estimated OD center). The first row shows retinal images without pathologies. The second row shows five retinal images that suffer from different types of retinal lesions. The third row shows the five retinal images that suffer from different types of retinal lesions and imaging artifacts where the proposed method fails

throughout an image, but this occurred for only one image out of the 121 tested from both databases (fifth image of the bottom row of Fig. 6).

Finally, the proposed technique still has several limitations. First, the proposed pattern matching is based on the assumption that there are visible blood vessels on OD. Another drawback of our approach is that it is based on the assumption that the OD is more or less brighter than the surrounding retinal pixels and, therefore, cannot handle retinal images whose OD is even darker than the surrounding pixels.

The proposed method achieved a success rate of 95.9% (i.e., the OD was detected correctly in 116 out of the 121 images contained in the DRIVE and STARE databases). In addition, the evaluation of our technique is close to that of the methods [6],[7] that rely on the retinal blood vessel.

IV. Conclusion

In this paper, a simple and computationally efficient algorithm for automatic OD detection has been presented. The proposed algorithm takes advantage of the powerful preprocessing techniques such as the contrast enhancement, Gabor wavelet transform, mathematical morphology and Earth Mover's distance as the matching process. The availability of a vessel extraction procedure is a necessary prerequisite for our technique, and the performances of this step directly affects the correct positioning of the OD.

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