Segmentation of Optic Disk for the Analysis of Diabetic Retinopathy System

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ABSTRACT

Nowadays, some of the most common cause of visual impairment, and blindness are because of diabetes retinopathy, hypertension, glaucoma. These diseases can be detected through regular ophthalmologic examination. However, due to population growth, the ophthalmologists and the experts needed for examination is a limiting factor. So, a system for automatic recognition of these pathological cases will provide a great benefit. Regarding this aspect, the method proposed for the detection of Optic Disc is based on mathematical morphology along with Principal Component Analysis(PCA). It makes use of different operations such as generalized distance function (GDF), the stochastic watershed,and geodesic transformations. The implemented algorithm has been validated on five public databases obtaining promising results.

***Index Terms*—**Generalized distance function, geodesic transformation, Optic Disc, Principal Component Analysis, Watershed transformation.

I INTRODUCTION

Diabetic retinopathy, hypertension, glaucoma and macular degeneration are nowadays some of the most common causes of visual impairment and blindness. Early diagnosis and appropriate referral for treatment of these diseases can prevent visual loss. All of these diseases can be detected through a direct and regular ophthalmologic examination of the risk population. However, population growth, aging, physical inactivity and rising levels of obesity are contributing factors to the increase of diseases, which causes the number of ophthalmologists needed for examination is a limiting factor. So, a system for automatic recognition of these pathological cases would provide a great benefit.

Regarding this aspect, optic disc (OD) segmentation is a key process in many algorithms designed for the automatic extraction of anatomical ocular structures, the detection of retinal lesions, and the identification of other fundus features. Initially, the OD location helps to avoid false positives in the detection of exudates associated with diabetic retinopathy, since both of them are spots with similar intensity[3]. Secondly, the OD margin can be used for establishing standard and concentric areas in which retinal vessel diameter measurements are performed by calculating some important diagnostic indexes for hypertensive retinopathy, such as central retinal artery equivalent (CRAE)[3] and central vein equivalent(CRVE)[3]. Thirdly, the relation between the size of the OD and the cup (cup-disc-ratio) has been widely utilized for glaucoma diagnosis.

Numerous OD segmentation methods, i.e., OD-boundary detectors, have been reported in the literature[4][5][6]. As for algorithms based on mathematical morphology, most of them detect the OD by means of watershed transformation, generally through marker-controlled watershed. The centroid of the largest and brightest object of the image is consider as an approximation for the locus of the OD and it is used as internal marker.

The method proposed in this paper is mainly based on mathematical morphology although includes a principal component analysis (PCA) in the preprocessing stage. The main steps of the method are the following:

First, the PCA is applied on the RGB fundus image in order to obtain a grey image in which the different structures of the retina, such as vessels and OD, are differentiated more clearly to get a more accurate detection of the OD. This stage is very important since it largely determines the final result.

Then, the vessels are removed through inpainting technique to make the segmentation task easier. Next, a variant of the watershed transformation, the stochastic watershed transformation, are implemented on a region of the original image. Finally, it must be discriminated which of the obtained watershed regions belong to the optic disc and which ones are not. A geodesic transformation and a further threshold are used to achieve that purpose.

This method provides robustness in each processing step. First, it is independent of the database thanks to using PCA. Secondly, it employs the grey-image centroid as initial seed so that not only the pixel intensity is taken into account. Thirdly, it makes use of the stochastic watershed in order to avoid sub-segmentation problems related to classical watershed transformation.

II METHODS

A. *Principal Component Analysis:*

The central idea of PCA is to reduce the dimensionality of a data set. This is achieved by transforming the image to a principal component space containing the most structural contrast and information. The first principal axis is the one with the greatest amount of contrast and information.

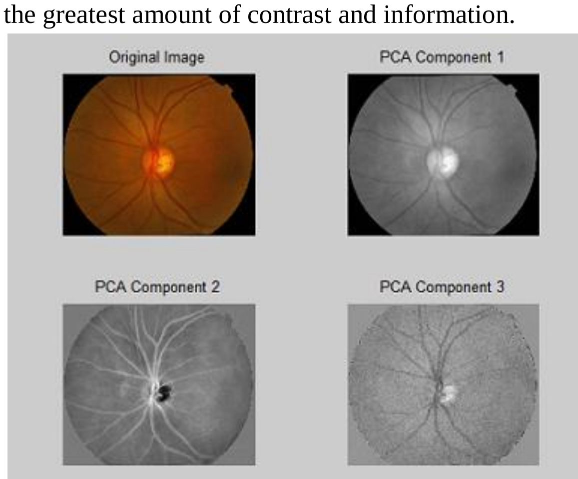

Fig 1.PCA components

The last principal axis represents the least amount of information such as noise and image artifacts .

In this case, the PCs are given by

$Z_k = \alpha_k' f = \alpha_{kR}' f_R + \alpha_{kG}' f_G + \alpha_{kB}' f_B$

$$\mathbf{\Sigma} = \begin{pmatrix} \sigma_R^2 & \sigma_{RG} & \sigma_{RB} \\ \sigma_{GB} & \sigma_G^2 & \sigma_{GB} \\ \sigma_{RB} & \sigma_{GB} & \sigma_B^2 \end{pmatrix}$$

Where,

$f(x) = (f_R(x), f_G(x), f_B(x))$

$k \in \{1,2,3\}$

$\sum$ - Covariance Matrix

B.*Inpainting:*

Inpainting algorithms are used in diverse applications, from the restoration of damaged photographs to the removal/replacement of selected objects. These algorithms usually try to fill selected parts of an image by propagating external information so that structure continuity is preserved.

Let a binary image $\Omega(x)$ stand for the region to be inpainted $\partial\Omega$ and for its boundary. For each $\partial\Omega$-pixel ,x, the inpainted pixel value is computed as

$$P(\mathbf{x}) = \frac{\sum_{k=1}^{n} \frac{P_k(\mathbf{x})}{l_k}}{\sum_{k=1}^{n} \frac{1}{l_k}}$$

Where P_k denotes the pixel values in a 5×5 neighborhood of the pixel under consideration, n is the number of neighboring pixels, and l_k is the distance between the pixel x and each neighboring pixel.

C.Morphological Operators:

Mathematical morphology is a nonlinear image processing methodology based on minimum and maximum operations whose aim is to extract relevant structures of an image.

The two basic morphological operators are:

$$\text{Dilation} : [\delta_B(f)](\mathbf{x}) = \max_{b \in \breve{B}(\mathbf{x})} f(\mathbf{x} + \mathbf{b})$$
$$\text{Erosion} : [\varepsilon_B(f)](\mathbf{x}) = \min_{b \in \breve{B}(\mathbf{x})} f(\mathbf{x} + \mathbf{b}).$$

Their purpose is to expand light or dark regions, respectively, according to the size and shape of the structuring element. Those elementary operations can be combined to obtain a new set of operators or basic filters given by

$$\text{Opening} : \gamma_B(f) = \delta_B(\varepsilon_B(f))$$
$$\text{Closing} : \varphi_B(f) = \varepsilon_B(\delta_B(f)).$$

***D.** Grey-Image Centroid:*

It marks the center part of the image containing OD. The centroid of a grey-level image can be calculated based on the generalized distance function(GDF). This algorithm is focused on modifying the classic two-pass sequential distance function so that:

1) edge cost is taken into account;
2) raster and anti-raster scans of the image are iterated until stability.

E.Stochastic Watershed Transformation:

Watershed transformation[8] is a segmentation technique for gray-scale images. This algorithm is a powerful segmentation tool whenever the minima of the image represent the objects of interest and the maxima are the separation boundaries between objects. Due to this fact, the input image of this method is usually a gradient image. In mathematical morphology, the gradient g(f)(x) of an image f(x) is obtained as the pointwise difference between a unitary dilation and a unitary erosion, i.e.,

$$\varrho(f)(\mathbf{x}) = \delta_B(f)(\mathbf{x}) - \varepsilon_B(f)(\mathbf{x}).$$

III PHASES OF OD SEGMENTATION

A.Preprocessing:

1) PCA:

In this work, the use of a new grey-scale image is proposed. Specifically, it is calculated by means of PCA because this type of analysis maximizes the separation of the different objects that compose a image so that the structures of the retina are better appreciated.

2)Image enhancement

The nonuniform illumination of this grey image is also corrected and its contrast is increased through a local transformation. The transformation for shade correction is given by the expression

$$\Gamma(f)(t) = \begin{cases} \frac{\frac{1}{2}(u_{\max}-u_{\min})}{(\mu_f - t_{\min})^r}(t - t_{\min})^r + u_{\min}, & \text{if } t \leq \mu_f \\ \frac{-\frac{1}{2}(u_{\max}-u_{\min})}{(\mu_f - t_{\max})^r}(t - t_{\max})^r + u_{\max}, & \text{if } t > \mu_f \end{cases}$$

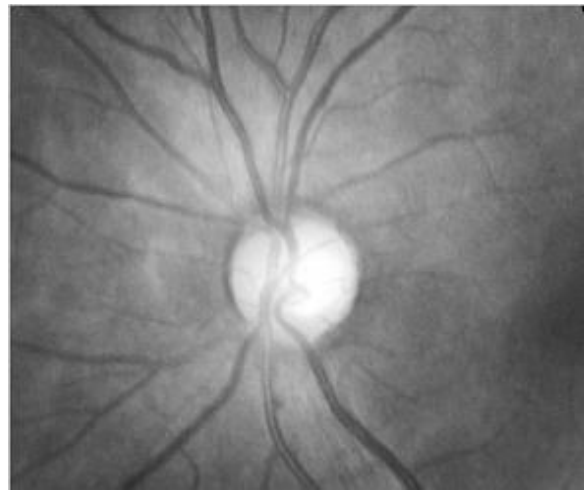

Fig 2.Enhanced image

3) Inpainting

Its aim is to extract the OD-boundary more precisely and to reduce the existing borders within the OD which increase the risk of sub-segmentation. A rough segmentation of the vessels is performed by means of a k-means clustering from the green band of the original image with a k value equals to 3.

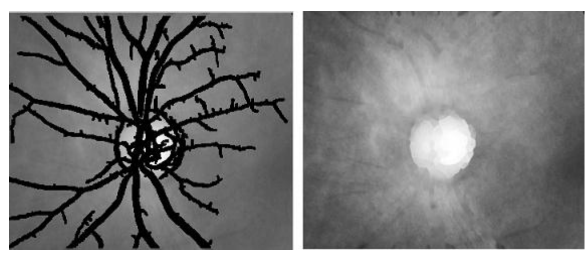

Fig 3. A)vessels to be inpainted,
B) inpainted image.

This algorithm classifies the image pixels in three clusters so that each pixel belongs to the cluster with the nearest mean. Then, two of the three obtained clusters are defined as vessel. Three classes are required because thick and thin vessels may be very different. Afterwards, a unitary morphological dilation of the segmented vessels yields the final vessel mask. The purpose of this operation is to make sure that the vessels will be contained in the mask.

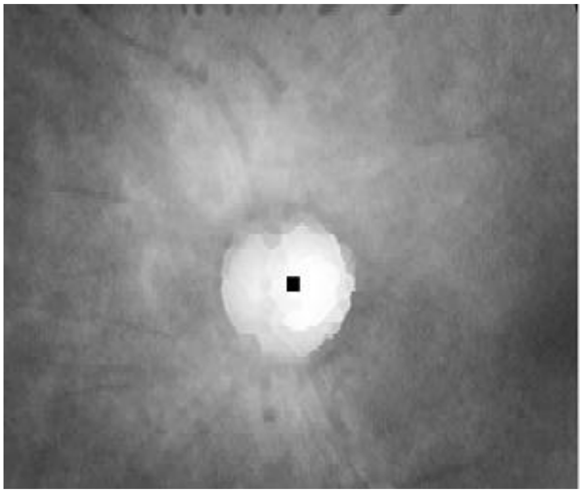

Fig 4. Grey image centroid

B.OD Segmentation

1)Stochastic watershed transformation:

The segmentation method makes use of the stochastic watershed. This transformation uses random markers to build a probability density function of contours, according to which is then segmented by volumic watershed for defining the most significant regions. However, in the marker definition not only internal markers (that specify what is the object of interest) are needed, but also an external marker which limits the area to be segmented.

Fig 5. segmented image

C.Postprocessing:

Once the region of interest has been obtained, the result must be fitted to eliminate false contours,which are detected due generally to the blood vessels that pass through the OD. The inpainting technique was performed to remove most of them, as previously mentioned, however some irregularities can still be appreciated in the final region contour.

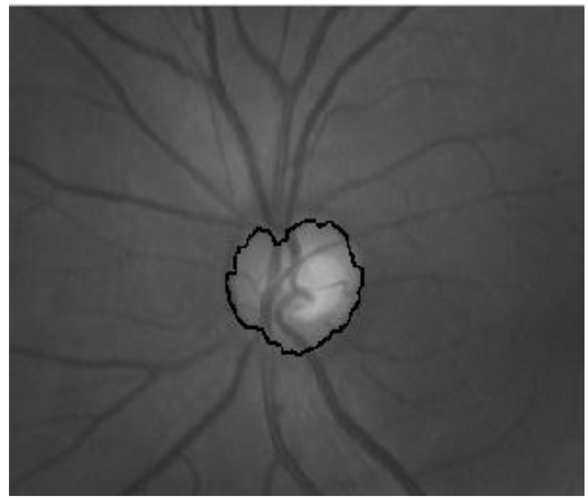

Fig 6.circular approximation

In this work, the OD-contour has been estimated as a circle. The main reason for fitting the OD by a circle is because this algorithm will later be used to establish a zone of the retina concentric to the OD-margin according to a standard protocol with the aim to perform vessel diameter measurements. The fit is performed by means of Kasa's method which lets calculate the center and the radius of the circle that better is adapted to a binary region through least squares.

IV RESULT & DISCUSSION

The validation of the method has been carried out on five public databases: DRIONS , DIARETDB1 , DRIVE , MESSIDOR , and ONHSD. Variability between fundus images in color, intensity, size,presence of artefacts, etc., makes each state-of-the-art method uses a different input image: green and red band of the original RGB image, or even a combination of both of them. However, due to this fundus image variability, they do not always provide the desired results. Therefore a PCA, able to maximize the separation between the different objects of the image, has been proposed in this paper as a more appropriate input image.

V CONCLUSION

In this paper, a new approach for the automatic detection of the optic disc has been presented. First, it is focused on the use of a new grey image as input obtained through PCA which combines the most significant information of the three RGB components. Secondly, several operations based on mathematical morphology are implemented with the aim of locating the OD. For that purpose, both stochastic and stratified watershed as well as geodesic transformation have been used. The algorithm has been validated on five different public databases obtaining promising results and improving the results of other methods of the literature.

The final goal of the proposed method is to make easier the early detection of diseases related to the fundus. Its main advantage is the full automation of the algorithm since it does not require any intervention by clinicians, which releases necessary resources (specialists) and reduces the consultation time, hence its use in primary care is facilitated.

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