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Retinal network characterization through fundus image processing: Significant point identification on vessel centerline

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ABSTRACT

This paper describes a new approach for significant point identification on vessel centerline. Significant points such as bifurcations and crossovers are able to define and characterize the retinal vascular network. In particular, hit-or-miss transformation is used to detect terminal, bifurcation and simple crossing points but a post-processing stage is needed to identify complex intersections. This stage focuses on the idea that the intersection of two vessels creates a sort of close loop formed by the vessels and this effect can be used to differentiate a bifurcation from a crossover. Experimental results show quantitative improvements by increasing the number of true positives and reducing the false positives and negatives in the significant point detection when the proposed method is compared with another state-of-the-art work. A sensitivity equal to 1 and a predictive positive value of 0.908 was achieved in the analyzed cases. Hit-or-miss transformation must be applied on a binary skeleton image. Therefore, a method to extract the vessel skeleton in a direct way is also proposed. Although the identification of the significant points of the retinal tree can be useful by itself for multiple applications such as biometrics and image registration, this paper presents an algorithm that makes use of the significant points to measure the bifurcation angles of the retinal network which can be related to cardiovascular risk determination.

1. Introduction

Retinal structure characterization is a fundamental component of most automatic retinal disease screening systems [1]. It is usually a prerequisite previous to carrying out more complex tasks as identifying different pathologies. In general, anatomical structures are segmented through fundus image processing and then certain features are extracted from them to characterize each pathology. One of the most important anatomical structures of the fundus is the vascular network that corresponds to the retinal blood vessels. Morphological attributes of retinal blood vessels, such as length, width, tortuosity and/or branching pattern and angles can be used for diagnosis, screening, treatment, and evaluation of various cardiovascular and ophthalmologic diseases [2].

In the vessel centerline there are three types of significant points: terminal, bifurcation and crossing. The detection of significant points in the retinal vascular tree increases the information about the vascular structure allowing its use for medical diagnosis. In particular, the identification of the vascular bifurcations and crossovers on the vascular network is helpful for predicting cardiovascular diseases and can also be used as biometric features or for image registration [3].

This paper focuses on the identification of the significant points as a means of defining and characterizing the retinal vascular network. In general, the significant points of the vascular network are detected on vessel centerline, also called vessel skeleton. The centerline can be obtained after a skeletonization process of the vessels previously segmented or through some method by which the skeleton is directly obtained. The main disadvantage of the first approach is that an inaccurate vessel segmentation may result in errors in the skeletonization. Motivated by that reason, this paper describes an approach to determine the retinal skeleton in a direct way through stochastic watershed transformation. Then, a new method to distinguish the different types of significant points on the retinal skeleton is presented. Finally, the proposed method is used as a necessary step before measuring bifurcation angles through the orientation vectors of each branch of the vascular tree.

In the literature there exist different attempts for significant point detection. Some of them are only based on bifurcation location [4] or

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on detecting bifurcations and the most simple intersections [5]. Other works take into consideration more types of crossovers since it is the most challenging part and try to distinguish between them and bifurcations. The most common approach is to center a fixed-size circular window on all bifurcations and check the number of intersections between the vessel centerline and the circular window [6,7]. However, it causes that the large vessel crossovers are detected as two bifurcation points. Bhuiyan et al. addressed this problem by considering the width of the junction [3] and Calvo et al. by combining local and topological information [8].

Referring to vessel extraction techniques, they can be mainly divided into four categories: edge detectors, matched filters, pattern recognition techniques and morphological approaches. A more extensive classification can be found in [1]. Most edge detection algorithms assess changes between pixel values by calculating the image gradient magnitude and then it is thresholded to create a binary edge image [9,10]. Matched filters are filters rotated in different directions in order to identify the cross section of blood vessels [11,12]. Pattern recognition techniques can be divided into supervised and unsupervised approaches. Supervised methods, such as artificial neural networks [13] or support vector machines [14,15], exploit some prior labelling information to decide whether a pixel belongs to a vessel or not, while unsupervised algorithms perform the vessel segmentation without any prior labelling knowledge [16]. Morphological processing is based on vessels characteristics known a priori (line connected segments) and combines morphological operators to achieve the segmentation [17–19]. Although most of the state-of-the-art methods look for detecting all vessel pixels of the vascular tree, there are also some attempts based on finding the vessel skeleton, e.g., those based on shortest path connection [20], on matched filters [21], on ridge descriptors [22] or on the application of the classical marker-controlled watershed [23,24], which differs to the stochastic watershed that is applied in this work.

The main contribution of this paper is the presentation of a complete methodology for significant point detection of the retinal vascular tree from a fundus image. It includes the vessel centerline extraction and the differentiation between bifurcations and complex crossings, which is a challenging and key process for a correct vessel tracking. In addition, despite the lack of public databases with manual-detected points to be used as ground truth, quantitative quality parameters were calculated.

The rest of the paper is organized as follows: Section 2 describes materials and methods. Section 3 presents an approach for vessel centerline extraction in retinal images. Section 4 addresses the algorithm to detect significant points on the vessel centerline. That algorithm is used to select the bifurcation points existing in the image and measure the bifurcation angles as explained in Section 5. Section 6 shows the results of the methods presented in Sections 3–5. Finally, Section 7 closes the paper with conclusions and future lines of work.

2. Materials and methods

2.1. Material

In this work, three different public databases were used: DRIVE [25], STARE [11] and VARIA [26]. DRIVE and STARE databases were used in the validation of the method for vessel centerline detection and all of them in the validation of significant point identification.

DRIVE database is composed of 40 retinal images (565×584 pixels) belonging to diabetic subjects. For each image, a mask image that delineates the field of view is provided as well as manual segmentations of the blood vessels. STARE database is a set of 20 images (700×605 pixels) along with two hand-labelled vessel network provided by different experts. VARIA contains 233 images, from 139 different individuals, with a resolution of 768×584 pixels.

2.2. Morphological operators

Mathematical morphology is a non-linear image processing methodology based on minimum and maximum operations, which can be used to extract relevant structures of an image f [27]. This is achieved by probing the image with another known shape B called structuring element (SE). The result of the single operation also depends on the choice of B. The two basic morphological operators are: *dilation*, $\delta_B(f)$, and *erosion*, $\varepsilon_B(f)$. Their purpose is to expand light or dark regions, respectively, according to the size and shape of the SE. Those elementary operations can be combined to obtain a set of basic filters: *opening*, $\gamma_B(f)$, and closing, $\varphi_B(f)$. Light or dark structures are respectively filtered out from the image by these operators regarding the SE chosen.

The method proposed in this paper for vessel centerline detection applies these basic filters directly, or uses them to derive more complex operators, such as:

- *Dual top-hat transformation*, $\rho_B(f) = \varphi_B(f) - f$, is used to extract contrasted dark components with respect to the background.
- *Close-hole operator* fills all holes in an image f that do not touch a boundary image. For a gray-scale image, it is considered a hole any set of connected points surrounded by connected components of value strictly greater than the hole values. This operator is defined as $\psi^{ch}(f) = [\gamma^{rec}(f^c, f_\partial)]^c$, where $\gamma^{rec}(g, f)$ is the *reconstruction by dilation* of an image f (marker) which is contained within an image g (reference), f^c is the complement image (i.e., the negative) and f_∂ the image boundary.
- *Reconstruction by dilation*, $\gamma^{rec}(g, f) = \delta_g^{(i)}(f)$, is the successive geodesic dilation of f regarding g up to idempotence, so that $\delta_g^{(i)}(f)$ represents the *geodesic dilation* and $\delta_g^{(i)}(f) = \delta_g^{(i+1)}(f)$. The *geodesic dilation*, $\delta_g^{(i)}(f) = \delta_g^{(1)}\delta_g^{(i-1)}(f)$, is the iterative unitary dilation of f regarding g, being $\delta_g^{(1)}(f) = \delta_B(f) \wedge g$.

2.3. Stochastic watershed transformation

Watershed transformation is a segmentation technique for gray-scale images [28]. 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 $\varrho(f)$. However, one problem of this technique is the over-segmentation, which is caused by the existence of numerous local minima in the image normally due to the presence of noise. One solution to this problem is using marker-controlled watershed, $WS(\varrho)_{f_{mrk}}$, in which the markers f_{mrk} artificially impose the minima of the input image. Nevertheless the controversial issue consists in determining f_{mrk} for each region of interest. Note that the use of a limited number of markers along with the complex morphology of the retinal vascular network can also cause that some parts of it are not detected (sub-segmentation). Therefore, the choice of the correct markers is crucial for the effectiveness and robustness of the algorithm.

The stochastic watershed is used to solve the sub-segmentation conflict [29]. In this transformation, a given number M of marker-controlled-watershed realizations are performed selecting N random markers to estimate a probability density function (*pdf*) of image contours and filter out non-significant fluctuations. The results of the different realizations are averaged by Parzen window method [30]. Obtaining a *pdf* of the contours of the watershed regions facilitates the final segmentation, providing robustness and reliability since the arbitrariness in choosing the markers is avoided. Afterwards, it is