Retinal Vessel Tree Segmentation using a Deformable Contour Model

L. Espona, M.J. Carreira,
Electronics and Computer Science Dpt.
University of Santiago de Compostela
Santiago de Compostela (Spain)
luciaep@usc.es, mjose@dec.usc.es

M.G. Penedo, M. Ortega
Computing Dpt.
University of A Coruña
A Coruña (Spain)
mgpenedo@udc.es, mortega@udc.es

Abstract

This paper presents an improved version of our specific methodology to detect the vessel tree in retinal angiographies. The automatic analysis of retinal vessel tree facilitates the computation of the arteriovenous index, which is essential for the diagnosis several eye diseases. The developed system is inspired in the classical snake but incorporating domain specific knowledge, such as blood vessels topological properties. It profits from the automatic localization of the optic disc, the vessel creases extraction and, as a recent innovation, the morphological vessel segmentation, all developed in our research group. After researching and testing our system, the parameter configuration has been enhanced. Significantly better results in the detection of arteriovenous structures are obtained, keeping a high efficiency, as shown by the systems performance evaluation on the publicly available DRIVE database.

1. Introduction

The automatic analysis of blood vessels is becoming more and more important in many scientific researches related to vascular features. The early diagnosis of several pathologies, such as hypertension, arteriosclerosis or diabetic retinophaty could be achieved analysing the vascular structures. The Digital Colour Fundus Photographs here used are a non invasive and innocuous technique to obtain the retinal vascular tree. The retina arteriovenous index (AV index), which indicates the relation between retinal arteries and veins calibers, is crucial to diagnose these illnesses and evaluate their consequences.

The eye fundus photographs are 2-D medical images which present inadequate contrast, lighting variations and remarkable noise influence. Another drawback is the anatomic variability, affecting both the retinal background texture and the blood vessels structure. Blood vessels particular features make them complex structures to detect as the color of vascular structures is not constant even along the same vessel. Their complex tree-like geometry includes bifurcations and overlaps that may mix up the detection system. Nevertheless, the linearity or the tubular shape could make the contour detection easier. As blood vessels segmentation becomes essential for several medical diagnostic systems, numerous research efforts have been done in this field [7]. The vascular detection has been tackled from different approaches and techniques including pixel-based approaches [6] or classification methods [9]. The deformable contour models are widely followed in vessel tracking, even combined with other techniques [11].

This work presents an innovative methodology, which incorporates domain specific knowledge into the generic contour deformable model. The snake model is specialised with the blood vessels topological properties, which determine the detection system behaviour. We have taken a great advantage of the automatic localization of the optic disc [1], the vessel creases extraction [2] and enhancement [8] previously developed in our research group. In this new version, our model also profits from a morphological segmentation recently introduced [3]. After researching and testing our system, we found a parameter configuration that significantly improves our systems performance. More accurate results in the detection of arteriovenous structures are achieved, especially in terms of sensitivity, as it will be shown in the results section. After these improvements, the execution time costs keep being low, which is very important for the arteriovenous index calculus, where accurate and fast measures of vessel diameters are needed. Next we will explain briefly our vessel tree detection system, focusing on the new included features.

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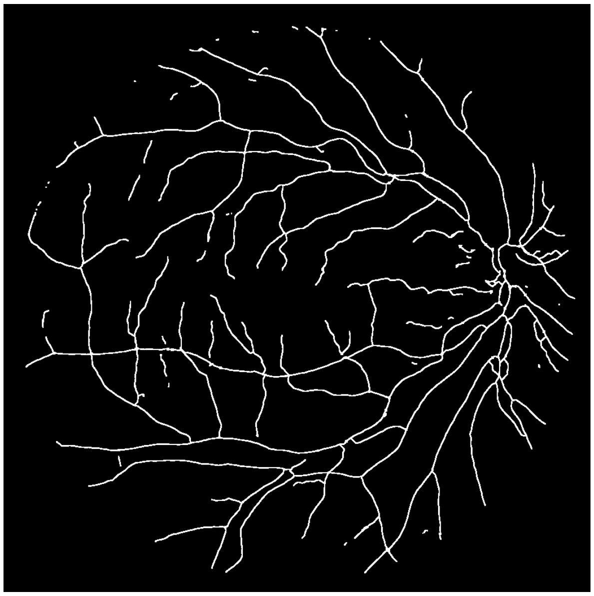

Figure 1. : Vessel creases extraction.

2. Vessel Tree Detection System

The developed model for the detection of the vessel tree is based on a deformable contour guided by vessel creases. This section will begin with a brief introduction of the creases extraction process, it will continue with the vessel morphological segmentation presentation and then the classical deformable contour model will be summarized. Once the theoretical fundamentals have been presented, our snake model will be described, mainly analysing the innovations and its resulting behaviour.

2.1. Creases Extraction

A crease is a continuous area of points on the image, shaping a highest or a lowest level in its environment. In this way, blood vessels can be considered as regions which form an extreme and tubular level on their neighbourhood. This fact allows us to locate the vessels by using the creases position. Thus, the creases extraction [2] is a crucial step in the snake evolution. We have enhanced the creases image such that the feature points (ridge endings and bifurcations) are adequately connected to get rid of discontinuities along the centerline [8].

In subsection 2.3 we will explain how the creases extraction determines the initial snake, acts as external energy guiding the contour expansion and contributes to the the edge image enhancement .

2.2. Morphological Vessel Segmentation

The segmentation obtained by the morphological technique is completely automatic and quite accurate [3]. Even so, the precision achieved is not enough for the final application, so it will be used as an *auxiliary segmentation* to improve our model performance. This

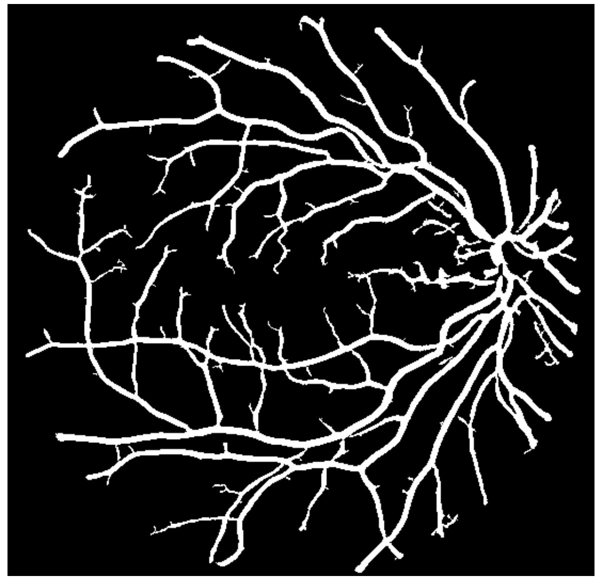

Figure 2. : Morphological vessel segmentation.

segmentation is obtained using an algorithm based on the proposal by Condurache and Aach [3], which is adapted to the specific domain of the retinal vessel segmentation. The developed algorithm exploits the connectivity property of the retinal vascular tree and it consists on two phases: the vascular network enhancement and the vessel tree extraction. In the first phase, the image is preprocessed in order to increase the contrast difference between vessels and background and to reduce background noise and vascular reflex. After that, the vascular structures are enhanced considering its morphological features by a vessel membership probability function. In the second phase, the vessels pixels are selected by an hysteresis-based thresholding technique according to the probability previously assigned. Finally, the groups of connected pixels initially selected as vessels that do not reach a minimum size threshold, are removed as they are supposed to correspond with lesions or noise.

We profit from this auxiliary segmentation to incite the snake expansion inside the vascular structures segmented by these techniques but not detected in the creases extraction. We also calculate this auxiliary segmentation edge image and add it to the original edge image in order to enhance it by closing some discontinuities.

2.3. Deformable Contour Model

Our approach is based on the deformable contour model, also called snake model proposed to segment objects in 2-D images [5]. Our snake model will not consider the internal energy as the vessel shape may be very tortuous. Thus, the **external energy** affecting the snake will be defined as a set of five energies and weighting factors [4]:

$$\varepsilon_{ext} = \gamma\varepsilon_{edge} + \delta\varepsilon_{cres} + \nu\varepsilon_{dir} + \sigma\varepsilon_{mark} + \omega\varepsilon_{dif} \qquad (1)$$

The first term ε_{edge} corresponds to the edge distance energy that helps the snake advance of nodes close to vessel boundaries but it also stops them when they reach a minimum, that is, when they reach an edge point. The edges of the auxiliary segmentation result are added to the original edge image to close some discontinuities that often appear near small vessels bifurcations. In addition, the edge pixels crossed by a crease are removed since it usually correspond to bifurcations, overlaps or noise effects.

The second term ε_{cres} corresponds to the creases distance energy that drives the snake along the arteriovenous structure and blocks it if a maximum distance threshold is reached. Now this block only takes place when in addition to reach the creases distance threshold, the area is considered as background by the auxiliary segmentation. Therefore, the snake is able to segment vessels detected by the auxiliary segmentation, even when no creases were extracted for this vascular structure. The distance threshold is more restrictive since auxiliary segmentation information is available. The lower threshold value decreases the time costs of the creases distance energy calculation.

The inflate pressure ε_{dir} is the strongest expansion force of the snake and determines the movement direction assigned to each node. The fourth term ε_{mark} is the marker energy that constraints the snake dilation as nodes are moving to avoid self overlapping or turning back. The difference energy ε_{dif} reinforces the precision of the snake expansion as it hints the nodes to occupy positions different from its neighbours situations.

Based on the external energy described in equation (1), different node states are defined. The *crease* nodes are located in the vessel crease and make the snake advance longitudinally. The *edge* nodes are placed close to vessel boundaries and tend to become stable when reaching the vessel edge. The *normal* nodes contribute to the snake expansion in an intermediate direction.

	Accuracy	Sensitivity	Specifity	Time (s)
Improved Snake	**0.9352**	0.7436	0.9615	38.4
Espona et al. [4]	**0.9316**	0.6634	0.9682	32.1
Staal et al. [10]	**0.9441**	0.7190	0.9770	900.0
Mendoça [6]	**0.9463**	0.7315	0.9781	150.0
Soares et al. [9]	**0.9466**	—	—	180.0
2ndObserver	**0.9473**	0.7760	0.9725	7200.0

Table 1. : Results for the presented method (Improved Snake), different segmentation methods and an independent observer (2ndObserver), with the same human segmentation as ground truth.

The snake initialisation consists on tracing a circumference surrounding the optical nerve by an automatic localization system [1]. The intersections of this circumference with creases will be the *seed nodes* of the snake. After this initialisation, the snake evolves following a deterministic and iterative algorithm to minimise these energy functions locally until the stability is reached. Each active node tries to move towards a lower energy position until it becomes irreversibly inactive when arriving to an edge or due to the control operations performed to avoid problems derived from edge discontinuities [4].

3. Results

In this section we report the results of vessel segmentation obtained by our snake model on medical images from the publicly available DRIVE database [10]. The test set here used contains 20 JPEG compressed images acquired using a Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). The manual segmentation results and the FOV mask images for computing the performance measures were provided together with the DRIVE database. The model has been implemented in C++ and executed on a PC with a T2400 Core Duo processor (1.83 GHz) and 2GB memory. Our snake-based system performance measures (Table 1) consider only the FOV region without the optic disc.

After analysing in detail the DRIVE public image database, we adapted the creases extraction configuration to the test images set. These new parameter values together with the other modifications we developed, represent a large improvement in our system performance (Table 1). For each image, the average time needed for the whole vessel detection process is 38.4 seconds, 4.0 correspond to auxiliary segmentation.

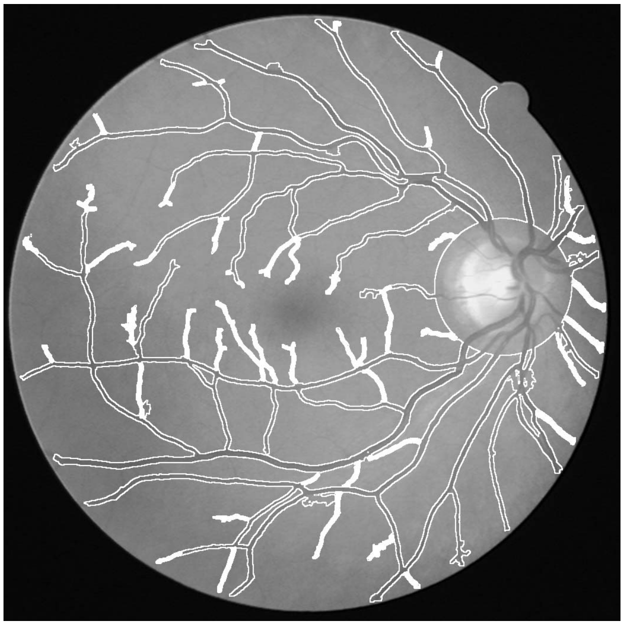

Figure 3. : Segmentation results. New detected vessels filled in white

4. Conclusions and Discussion

In conclusion, we improved our snake-based methodology to segment the vessel tree on retinal digital images as the high precision achieved show (Table 1). The system reaches an average accuracy of 0.9352 in less than 40 seconds. The precise and efficient segmentation obtained is suitable for a wide range of utilities related to retinal or vascular pathologies, even for large screening and real-time applications. To set an example, removing the vessel tree detected could make the location of retinal background lesions easier. A extreme efficiency in terms of execution time cost has been achieved compared with the tedious and long manual detection (about two hours each image). Other state-of-the-art segmentation methods have much higher time costs, although they obtain similar accuracy values (Table 1). The performance results are not equally computed, as we ignore the small area of the optic disc because it is not important for the applications being analysed. Nevertheless, including these vessels will only make results even better.

The segmentation accuracy is similar to human performance, although it is not able to segment some very thin vessels. Actually, very thin vessels are not essential for the AV index calculation, since the ophthalmologists are only interested on main vessels leading to reproducible results. Our researching efforts are now mainly focused on automatically tuning the parameters depending on the image and on enhancing and optimising the energy minimisation.

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