Vascular Tree Segmentation in Retinal Angiographies: Deformable Contour Model Approach

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Abstract: This paper describes a new method to detect the retina vascular tree. This detection is performed by a deformable contour model in angiographic retinal images. The generic deformable contour model is here redefined to obtain a more accurate segmentation by considering specific features of these vascular structures, mainly the anatomical landmarks that a crease extraction technique obtains. Results on sample images are promising, making it easier the computation of the AV index, very important for the diagnosis of several pathologies.

Key–Words: Snakes, Retinal Fundus images, Segmentation, Tracing, Retinal Vasculature.

1 Introduction

The automatic analysis of blood vessels is becoming more and more important. Many clinical investigations and scientific researches work on potential clinical applications related to vascular features. In particular it has become very significant for diagnosis of wide range of pathologies. The vascular tree from the retinal angiographies shows early symptoms of several diseases, such as arterial hypertension or arteriosclerosis. As a result, the retina arteriovenous index (AV index) takes a vital priority in order to diagnose these illnesses and evaluate their consequences. That is the reason why a precise and robust estimation of this parameter is usually needed. This paper deals with the research of a vascular tree detection system, which would constitute the first step to allow the AV index measuring [1].

As blood vessels segmentation becomes essential for several medical diagnostic systems, numerous research efforts have been done in this field. The vascular detection has been tackled from different approaches and techniques including pattern recognition, model-based approaches, tracking-based techniques, artificial intelligence or neural networks. Segmentation methods vary depending on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors [2].

The retinal angiographies are 2-D grayscale medical images quite problematic. The main difficulties facing us are the inadequate or insufficient contrast and remarkable noise influence mainly due to its complex acquisition. Another drawback is the anatomic variability depending on the particular patient, affecting both the retinal background and the blood vessels structure. Blood vessels particular features make them complex structures to detect as the grey level of vascular structures is not constant even along the same vessel. Their tree-like geometry is often strange and complicated, including bifurcations and overlaps that may mix up the detection system. Nevertheless, other characteristics, like the linearity or the tubular shape, could make the contour detection easier.

In this research field, the work of Zana and Klein [3] is based on the idea that the vessels exhibit an approximately Gaussian cross section shape and they are piece-wise linear following a tree-like pattern. They also consider that they have a certain width and they cannot be too close together. From these traits, morphological filtering based algorithms are designed for classifying the vessel pixels.

Shen et al. [4] in their real-time vessel tracing work, enhance an intensity based model for separating vessel and non-vessel pixels. To perform a more complete separation they use the powerful structural information provided by the two prominent vessel bounds. Thus, for each grayscale minima detected, areas on either side of the minima can be searched to find edges by looking for oppositely signed derivatives. In addition to consider this one-pixel wide cross sectional profile, they filter the points based on the distance be-
between the edges. This method suffers from its low selectivity as only 1D properties of vessels are used.

There are other properties of vessels that can be used to reduce the number of false positives and allow us to expand into 2-D models. One such property is the observation that vessels are locally straight over short distances. Can et al. [5] detect vessel boundaries by means of a rotated kernels set that responds when placing over a vessel edge in its corresponding direction. Incrementing the kernel length results in a more sensitive detection but this cannot be done indefinitely given the vessel curvature and the computation cost time.

Such as both described above, pixel processing methods have generally computational needs that scale sharply with image size, and are usually unsuitable for fast real-time processing without special hardware. The dyed blood reflux constitutes an added difficulty for the segmentation process. High resolution fundus photographs often display a central light reflex caused by a reflection from or below the vessel surface, so that vessels appear to be hollow. Then the walls of the vessels appear as dark pixels but the centre lighter, sometimes as light as the background itself. Gao et al. [6] proposed a model to specifically handle this phenomenon. Intensity profiles over vessel cross-section have been modelled combining twin Gaussian functions representing the entire vessel and the reflex.

Cornforth et al [7] accomplish the detection of blood vessels using wavelet transforms combined with segmentation methods. The method used include supervised classifier probabilities and adaptive threshold procedures, as well as morphology-based techniques. They achieve noise-robust and accurate identification of blood vessels in non-mydriatic camera images of the retinal fundus but they still need to fine tuning these algorithms on a larger data set.

Neural networks are attractive in medical image segmentation for using nonlinear classification boundaries and for their ability to learn. Nekovei and Sun [8] use a back-propagation network for the detection of blood vessels in X-ray angiography. This system does not extract the vascular structure, but it labels the pixels as vessel or non-vessel. The classification achieved is accurate but neural networks have the disadvantages that they have to be trained every time a new feature is introduced and the tuning of their performance is a difficult task.

Artificial Intelligence based methods perform well in terms of accuracy, but the computational complexity is much larger than some other methods. Rost et al. [9] have developed a knowledge-based system, called SOLUTION (Solution for a Learning Configuration System for Image Processing), designed to automatically adopt low-level image processing algorithms to the needs of the application. It aims to overcome the problem of extensive change requirement in the existing system to perform in a different environment. The system accepts task descriptions in high-level natural spoken terms and configures the appropriate sequence of image processing operators by using expert knowledge. In the present implementation, extraction process is limited to contours.

The contour deformable models are widely followed in vessel tracking. Toledo et al. [10] combine a probabilistic principal component analysis (PPCA) with a statistical snake for tracking non-rigid elongated structures. Probabilistic PCA technique is used to construct statistical image feature descriptions while snakes are used for global segmentation and tracking of objects. The statistical snake learns and tracks image features using statistical learning techniques. They manage to take profit of the particular advantages of each technique.

None of the models here summarized is individually fully adequate for all applications and the models presented are not all-inclusive. Even though many promising techniques and algorithms have been developed, vessel segmentation is still an open area for more research and much work remains to be done in this field. For further reading on medical image segmentation techniques, we refer to surveys as [2] and [11]. In the specific context of retinal digital fundus images, Fritzsche et al. [12] developed a rigorous survey about segmentation, tracing and analysis models. It also includes an algorithm classification and performance results evaluation.

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 vascular tree graph, composed by the vessels center-lines, obtained from a creases extraction system developed previously by our research group [13]. The system initialisation includes a preliminary treatment of the original image that is firstly re-sampled. It is possible to work at subpixel level just doubling the image dimensions with bi-cubic interpolation. This is very important for tasks such as the arteriovenous index calculus, where accurate measures of vessel diameters are needed. In fact, a remarkable enhancement of the accuracy in the detection of arteriovenous structures is achieved, as it will be shown in the results section.

Next we will explain our vessel tree detection system, beginning with crease extraction in order to perform the deformable contour evolution.
2 Vessel Tree Detection System

Our model for the detection of the vessel tree is based on a deformable contour guided by a vessel crease. This section will begin explaining the creases extraction process, as well as its usefulness for main vessel detection. Then the classical deformable contour model will be described. Once the theoretical fundamentals have been presented, our particular snake model will be analysed in depth. We will show our innovative contribution, presenting the new specific features and their resulting behaviour.

2.1 Creases Extraction

Amongst the many mathematical definitions of ridges and valleys [14], a crease may be defined as a continuous area of points on the image, shaping a highest or lowest level in its environment. In this way, when images are seen as landscapes, blood vessels can be considered as ridges or valleys, that is, regions which form an extreme and tubular level on their neighbourhood. This fact allows to locate the vessels by using the creases position (see Fig.1). The creases extraction is essential for the detection process, since it will determine the initial snake seed points. Furthermore, it will be considered as external energy guiding the contour nodes advance to a suitable snake expansion.

The creases image is obtained using the MLSEC-ST operator [15] (Multilevel Set Extrinsic Curvature based on the Structure Tensor). Given a function \( L : \mathbb{R}^d \rightarrow \mathbb{R} \), the level set for a constant \( k \) consist in a set of points \( \{ x \mid L(x) = k \} \). For 2D images \( (d = 2) \), \( L \) can be considered as a topographic relief or landscape, where the level sets are its level curves. The level curvature \( k \) can be defined, according to MLSEC-ST, through the slopelines, that is, the lines integrating the gradient vector field \( \vec{\omega} \), orthogonal to the level curves. For this purpose, the divergence operator is defined as follows:

\[
\vec{\omega} \cdot \nabla
\]

\[
k = - div(\vec{\omega}) = - \sum_{i=1}^{d} \frac{\delta \omega^i}{\delta x^i}, d = 2
\]  

(1)

where \( \omega^i \) is the \( i \)th component of \( \omega \), the normalised vector field of \( L : \mathbb{R}^d \rightarrow \mathbb{R} \).

\[
\vec{\omega} = \begin{cases} 
\frac{w/||w||}{||w||} & \text{if } ||w|| > 0 \\
O_d & \text{if } ||w|| = 0
\end{cases}
\]

(2)

where \( O_d \) is the \( d \)-dimensional zero vector. In order to obtain a more enhanced and homogeneous creaseness measure, the gradient vector field of the image is pre-filtered before applying the divergence operator. This filtering is based on the structure tensor or moment tensor [15]. In this way, several measures such as the confidence degree (Confidence), the minimum grey level (MinGrey), the deviation of a Gaussian smoothing (\( \sigma_{l} \)), or the minimum length (MinLenght) may be fine-tuned. Adjusting these values is a fundamental step to obtain high-quality results in all kind of images (see our model values in Table 1). In fact, the results from a well-defined image will be different than the results from a low-contrasted one [13].

![Figure 1](image_url) A retinal image with its creases overlapped in white. The creases all the vascular tree, corresponding to the vessel centerlines.

Once introduced the creases, we will see how they will be used in our snake model.

2.2 Deformable Contour Model

Our approach is based on the deformable contour model, also called snake model. This parametric model was proposed by Kass et al. [16] to segment the boundaries of objects in 2-D images. A snake or active contour may be defined as a parametric curve which can evolve to fit the shape of the desired structure. The snake representation by a function of the arc length \( s \) is:

\[
v(s) = (x(s), y(s))
\]

(3)

Once placed in the image, this curve performs an iterative contour adaptation in order to minimise its global energy. The energy function may be defined as:

\[
\int_0^1 \varepsilon_{\text{snake}}(s) = \int_0^1 \varepsilon_{\text{int}}(s)ds + \int_0^1 \varepsilon_{\text{ext}}(s)ds
\]

(4)

where \( \varepsilon_{\text{int}} \) represents the internal energy and \( \varepsilon_{\text{ext}} \) the external energy. The internal energy corresponds to the snake flexibility and elasticity. The external energy corresponds to the forces that drive the snake towards the edges of the shape to locate. It introduces
coupling of the snake to the image features. The contour deforms under the influence of internal and external forces until it becomes stable, reaching the minimum of its energy function.

Our snake model incorporates arteriovenous topological properties to achieve a better contour fitting. The deformable contour designed is discrete, so it can be seen as a polynomial closed contour composed by linked nodes. The workspace, that is the angiographic image, is also discrete, since the snake operates at pixel-level.

As pointed out in equation (4), the snake is usually modulated by internal and external energies. Our snake will be influenced only by external energies: as the vessel shape may be very tortuous, smoothness or bending control are pointless, and so the internal energy will not be considered.

Because of the guided evolution of our snake, three possible node states are defined: normal, crease and edge (see Fig.2). The nodes in the crease state are located in the vessel crease and they make the snake to advance along the vessel center line. The positions close to vessel boundaries are occupied by nodes in the edge state that tend to become stable when reaching the vessel edge. The rest of nodes are in the normal state and they contribute to the snake expansion in an intermediate direction. The state assignation will be updated at each iteration based on the external energy and also on the information from the node neighbourhood.

Thus, the external energy affecting the snake will be defined as set of energies and weighting factors:

\[
\epsilon_{ext} = \gamma \epsilon_{edge} + \delta \epsilon_{cres} + \nu \epsilon_{dir} + \sigma \epsilon_{mark} + \omega \epsilon_{dif}
\]  

(5)

The first term \(\epsilon_{edge}\) corresponds to the edge distance energy. After testing other filters (Sobel, Laplace...), the Canny Filter [17] was selected to obtain the edge image of the original angiography. The filter parameters have been adjusted so that they are appropriate on average for all images. Once the edge image is available, the energy map is calculated by assigning to each point its euclidean distance to the nearest edge. This energy 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:

\[
\forall v_i \epsilon_{edge} = dist(v_i, I_{edge})
\]

(6)

where \(v_i\) is a node and \(I_{edge}\) is the edge image.

The second term \(\epsilon_{cres}\) corresponds to the creases distance energy. As previously explained, a creases extraction is performed on the original angiography. The creases distance energy map is obtained from the crease image just in the same way as for the edges. This energy can be considered as an advance energy, since it drives the nodes placed near a vessel centerline, speeding up its advance along the arteriovenous structure:

\[
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\]

(7)

where \(v_i\) is a node and \(I_{cres}\) is the creases image.

The inflate pressure \(\epsilon_{dir}\) is the strongest expansion force of the snake. Each node has one assigned advance direction that determines the three adjacent possible positions (called A, B, and C) where it can move to (see Fig.3(a)). Offering this three alternatives avoids situations as the one shown in Fig.3(b), where a node can go through an edge and go out of the vessel boundary. The inflate pressure forces the node to move to the lowest energy position among these three.

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that self overlapping or turning back never happens. This energy forces the node to move always to a new position and blocks it when all its advance alternatives have been occupied before:

\[ \forall v_i \in \text{mark} = \begin{cases} 1 & \iff I_{\text{mark}}(v_i) = 255 \\ 0 & \text{otherwise} \end{cases} \quad (8) \]

where \( v_i \) is a node and \( I_{\text{crees}} \) is the creases image.

The difference energy \( \varepsilon_{\text{diff}} \) is defined to reinforce the control over the snake expansion. This energy hints the nodes to occupy positions different from its neighbours situations. This way, a higher precision is achieved since more different vessel boundary points are set:

\[ \forall v_i \in \varepsilon_{\text{diff}} = \begin{cases} 1 & \iff \text{dist}(v_i, v_{i-1}) + \text{dist}(v_i, v_{i+1}) = 0 \\ 0 & \text{otherwise} \end{cases} \quad (9) \]

where \( v_i \) is a node, \( v_{i-1} \) and \( v_{i+1} \) are the nodes placed before and after it in the snake contour, that is, its direct neighbours.

2.3 Contour Evolution

Once introduced the energy functions to take into account, we have to deal with the problem of the initial contour. Firstly, the creases and edge images are calculated on the original re-sampled image, as well as its corresponding energy maps. Next, a circle surrounding optical nerve is traced by the user (see Fig.5(a)). The seed point for each snake is obtained from the intersections of creases and this circle (see Fig.5(b)). At the moment, a tool for automatic setting seed points is being developed by our research team. In the short term, this tool is expected to be integrated with this system, and make human interaction unnecessary on this point. After its initialisation, the snake evolves to minimise these energy functions locally (see Fig.5(c)): each node tries to move towards a lower energy position. As it will be explained later, its movement depends not only on its own information, but also on its neighbours one. The evolution process is performed by a deterministic and iterative algorithm which consists on moving all the snake nodes once, inserting new nodes, updating the energy and the state for each node and carrying out control operations.

The snake contour can be seen as a polynomial composed by vertices and segments linking them. In this snake model, these vertices are called nodes, and at a given moment, each node has an assigned state, as well as a space position. As mentioned before, there are three possible node states: normal, crease and edge (see Fig.2). These states are updated at each iteration based on the external energies values and also on the information from its neighbourhood.

The crease state is assigned to nodes placed near vessel centre, that is on the corresponding crease. The nodes in the crease state are in charge of the snake advance along the vessel line. Therefore, they are strongly influenced by the inflate pressure and the crease distance energy terms. The nodes in the edge state are near vessel boundaries, that is close to edges. These nodes are supposed to be soon stabilised when arriving to an edge point. Naturally, the most significant energy energy term for edge nodes is the edge distance \( \varepsilon_{\text{edge}} \). As it can be considered an intermediate situation, the normal state corresponds to all nodes placed between the creases and the edges, far enough from both of them. These nodes are generally expected to change its state to edge, so the edge distance term \( \varepsilon_{\text{edge}} \) is more important than the creases distance one. Normal nodes could evolve into crease nodes...
only in a few situations such as bifurcations, where a new crease node is selected to guide the snake into the secondary vessel branch. This behaviour is modeled by sets of energy term weights associated to each node state. Their values will be shown in the results section.

As well as being in a state, every node is also active or inactive. Each node is created active, then it moves and changes its state until it becomes irreversibly inactive from whatever state. This inactivation takes place usually when the node arrives to an edge, but also when it can’t move to a new position (it is blocked by the marker map) or due to other control operations, that will be explained below. The black small squares of contour shown in Fig.2 represent inactive nodes. The system execution automatically ends when all nodes are inactive, that is, when the snake reaches the stability.

In summary, the energy for each possible node movement is calculated considering the energy terms values associated to the position and the weights associated to the node. Iteratively, each vertex is moved according to forces that work on it, that is towards the local minimum energy situation. Consequently, the whole contour expands and the snake flows inside the vessel covering the vascular branch.

To completely segment the vascular structure with enough detail level, it is necessary to make the snake grow. New nodes are inserted in the middle of the snake segments that exceed an euclidean distance threshold. This growing distance threshold should be enough to get an adequate detail level without decreasing too much the model efficiency. Later on, the influence of this parameter in controlling the snake evolution will be explained.

In addition to these deformation and growing processes, we perform control operations derived from vessel structural features. These control operations work considering the snake as composed by sequences of consecutive active nodes, called forward fronts. In Fig.2 a forward front composed by five nodes is shown. Each front is forced to have exactly one node in crease state: the node with lowest crease distance or highest edge distance.

The number of nodes that each front contains is periodically checked. When a front becomes too large, all its nodes are inactivated since it is considered as a flood. This situation occurs usually at the end of the vessels or when the vessel edge has a wide hollow (see Fig.6(a)). Once the flood is detected and stopped, the snake contour slightly shrinks and tries to delete the nodes placed out of the vessel (see Fig.6(b)). The nodes of very small fronts are also inactivated, as this situation corresponds to an small edge discontinuity (see Fig.6(b)).

At this point, we have to estimate two parameters as references to evaluate the front size: the maximum and the minimum vessel width. The maximum and the minimum number of nodes for each front, are the result of dividing these parameters by the growing distance threshold. A too high maximum vessel width may increase the floods (see Fig.6(a)), but a too little one could block the snake in a bifurcation (see Fig.6(b)). The minimum width is also critical: if it is too big, thin vessels are not detected (see Fig.6(c)), but if it is extremely small, it lets the nodes to get through to every edge discontinuity (see Fig.6(d)).

3 Results

This paper ends reporting results of vessel segmentation obtained by our snake model on medical images. The images used to evaluate the system have been obtained from three health centres of the Complejo Hospitalario Universitario de Santiago(CHUS) and also from the Hospital Oftalmológico Santa Teresa(USP). Currently, this system is still being developed, so only preliminary evaluations on sample images have been
done.

In the initialisation, the centre and the radius to get the seed points have been manually defined on each image. As explained before, we are working on automatising this step.

The creases extractor parameters (see Table 1) have been selected considering the characteristics of our images and the indications found in [13]. The snake parameters (see Eq. 4) have been empirically adjusted and their values are shown in Table 1. The energy term weights corresponding to each node state have been firstly estimated considering the expected behaviour of each node state and fine tuned after some tests.

As shown in Table 2, for all node states, the marker energy is the one with the heaviest weight (σ). Even if the other energy terms are lower, the snake must not advance over an already visited area. As normal nodes usually evolve to edge nodes, their assigned weights will be similar. The edge nodes have a significant weight (γ) for the edge distance energy, since we want them to raise quickly the vessel edge. On the contrary, the crease nodes should advance along the vessel, then the crease distance term will have a very heavy weight (δ). The inflate pressure (ν weight) will also influence more the crease nodes than the normal and the edge ones, to force them to expand the contour. The difference energy term (ω) will have a lower importance, because it is just a hint to decide the best movement option when the other energy factors are equal. Crease and normal nodes are more interested in going to new positions than the edge nodes, so they will have a heavier difference energy weight.

The number of iterations varies for each image, but in average 1800 iterations were needed to segment the whole vascular tree. Figure 7 shows some results.

Regarding to the efficiency, we just intend to show a rough time need estimation for each processing step (see Fig. 8) of our detection system. In the current developing state of our model, several changes and new additions are still expected. For this reason, an exhaustive analysis of computation costs would be useless.

Five images have been used, each of them with size of 1063x850 pixels originally (2126x1700 pixels resampled), and 256 grey levels. The model has been implemented in C++ and executed on a PC with two Pentium4 processors (1GHz) and 1Gb memory. I/O image operations and result display have been excluded from time costs. All efficiency measures have been estimated with the same snake parameters that were found to be quite suitable for all images (see Table 1).

After perform time measurements in three executions for each image, the average value obtained for the whole vessel detection process (Ttotal) is 29.8 seconds. The main part of this time (35.8%) is spent in resampling the image to double size using bicubic interpolation (Tres). The creases extraction (Tcr) is also a significant step in duration, as it roughly represents the 16.7% of the whole process. Another critical step

Table 1: Snake parameters (top) are expressed in pixels. The values assigned to max and min vessel width are not very restrictive and they allow the snake to detect vessels in a wide range of calibres. The grow threshold forces to create a new node in segments longer than 5 pixels. From these values, we can infer that a forward front will be composed of at least one node and at the most 28. The creases extraction parameters value (bottom) have been adjusted for normal-contrasted images according to [13].

<table>
<thead>
<tr>
<th>NODE STATE</th>
<th>WEIGHTS</th>
<th>Normal</th>
<th>Edge</th>
<th>Crease</th>
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<tbody>
<tr>
<td>ν</td>
<td>0.025</td>
<td>0.020</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>ω</td>
<td>0.003</td>
<td>0.001</td>
<td>0.003</td>
<td></td>
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<tr>
<td>γ</td>
<td>0.062</td>
<td>0.079</td>
<td>0.000</td>
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<tr>
<td>δ</td>
<td>0.010</td>
<td>0.000</td>
<td>0.045</td>
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<tr>
<td>σ</td>
<td>0.900</td>
<td>0.900</td>
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Table 2: Energy Terms Weights in Eq. 4 depending on Node State: The marker energy (σ weight) is the heaviest as it restricts the node movements independently of its state. Normal and edge nodes have similar weights, giving high importance to the edge energy (γ weight). Crease nodes are mainly influenced by the inflate pressure (ν weight) and the crease distance (δ weight).

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Table 3: Average execution times in seconds for the different steps of our vessel detection model (see Fig. 8) obtained from a set of equal-size grayscale images. Ttotal is the whole segmentation process time. Tres corresponds to resampling the original image to double size. Tcr represents the crease extraction and Ted the time spent in obtaining the edge image. The time costs of calculating the energy images for the creases is TcrEn and for the edges is TedEn. The snake evolution for an average of 1852 iterations is Tink.

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<th>Normal</th>
<th>Edge</th>
<th>Crease</th>
</tr>
</thead>
<tbody>
<tr>
<td>ν</td>
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<td>0.020</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>ω</td>
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<tr>
<td>γ</td>
<td>0.062</td>
<td>0.079</td>
<td>0.000</td>
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<td>δ</td>
<td>0.010</td>
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<tr>
<td>σ</td>
<td>0.900</td>
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Table 2: Energy Terms Weights in Eq. 4 depending on Node State: The marker energy (σ weight) is the heaviest as it restricts the node movements independently of its state. Normal and edge nodes have similar weights, giving high importance to the edge energy (γ weight). Crease nodes are mainly influenced by the inflate pressure (ν weight) and the crease distance (δ weight).

<table>
<thead>
<tr>
<th>NODE STATE</th>
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Table 3: Average execution times in seconds for the different steps of our vessel detection model (see Fig. 8) obtained from a set of equal-size grayscale images. Ttotal is the whole segmentation process time. Tres corresponds to resampling the original image to double size. Tcr represents the crease extraction and Ted the time spent in obtaining the edge image. The time costs of calculating the energy images for the creases is TcrEn and for the edges is TedEn. The snake evolution for an average of 1852 iterations is Tink.
is the Canny algorithm to obtain the edges ($T_{ed}$) since it needs approximately the 8%. Calculating the energy images takes a time directly proportional to the distance limit selected. A value of 7 pixels is here used, this means that the image pixels located more than 7 pixels far from an edge (or a crease) are ignored (maximum energy).

Because normally there are two edges and only one crease for each vessel, the distance energy image for the edges ($T_{edEn}$) consumes about the 4.6%, the double as for the creases ($T_{crEn}$ is the 2.4%). The seed points are immediately obtained from the creases, therefore its calculation is practically irrelevant for time costs.

The snake evolution itself ($T_{snk}$) is completed in 9.7 seconds (32.5%), after an average of 1852 iterations. Although this step always presents a quite short duration, the snake parameters have a significant incidence on it as they affect the number of nodes, hence the calculations per iteration. A lower grow threshold increases the density of contour nodes and the width vessel values (such as a small minimum or a large maximum) may result in a longer snake contour since they determine the range of detectable vessel structures. Besides, we would like to remark the possibility of optimise in the future certain algorithms (for example, resampling) and even parallelize some independent execution steps, such as the edge and crease extractions (see Fig.8).

4 Conclusions

In conclusion, we have developed an innovative methodology to segment the vessel tree on retinal angiographies. The classical snake model is here redefined with the incorporation of domain specific knowledge and information from the vascular tree graph obtained from a creases extraction system.

The reported results are very encouraging but we need to further test the system and investigate the possible ways to overcome the model small drawbacks. In all images, the segmentation presents very similar problems (see Fig.7). In most cases, the snake does not reach the end of the vessel. That occurs because we need to enhance control operations, such as shrinking the snake when detecting a flood. Very thin vessels are not detected by the snake, a problem that could be partially solved by a dynamical tuning of the vessel width parameter. Actually, thin vessels are not very important in the detection process since the accuracy required for ophthalmologists is quite low. In fact, they are only interested on main vessels detection to calculate the arteriovenous index.

Our researching efforts are mainly focused on automatically tuning the parameters depending on the image and on enhancing and optimising the energy minimisation.

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References


