DETERMINATION OF RETINAL NETWORK SKELETON THROUGH MATHEMATICAL MORPHOLOGY

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ABSTRACT

This paper describes a new approach to determine vascular skeleton in retinal images. This approach is based on mathematical morphology along with curvature evaluation. In particular, a variant of the watershed transformation, the stochastic watershed, is applied to extract the vessel centerline. Its goal is to obtain directly the skeleton of the retinal tree avoiding a previous stage of vessel segmentation in order to reduce the dependence between stages and the computational cost. Experimental results show qualitative improvements if the proposed method is compared with other state-of-the-art algorithms, above all on pathological images. Therefore, the result of this work is an efficient and effective vessel centerline extraction algorithm and can be useful for further applications and image-aided diagnosis systems.

***Index Terms*—** Retinal vascular skeleton, vessel centerline, mathematical morphology, curvature evaluation, stochastic watershed

1. INTRODUCTION

Retinal vasculature is able to indicate the status of other vessels of the human body. Classically, its study is included in the standard screening of any patients with diseases in which the vessels may be altered inasmuch as it is a non-invasive or minimally invasive procedure. Changes in retinal vessel features can be precursors of serious diseases such as cardiovascular diseases and stroke, among others. An analysis of retinal vessel features can assist in the detection of these changes and can allow the patient to take actions in early stages of the disease.

In general, the detection of retinal vascular network is necessary before analysing vessel features. The most common approach in the literature is a first stage of vessel segmentation, then the skeletonization of the detected vessels and finally the analysis of different features on the vascular skeleton as vessel calibre or bifurcation angles. The major drawback of this approach is the dependence of the different stages with the previous ones in addition to computational cost. Based on these facts, this paper is focused on obtaining the retinal skeleton in a direct way avoiding the segmentation stage. Its goal is to reduce the number of necessary steps in fundus image processing. As a consequence, this would also reduce the dependency of previous stages. Specifically, the method proposed for this purpose is mainly based on mathematical morphology along with curvature evaluation. Two main steps are involved: in the first step, the principal curvature is calculated on the retinal image. In the second step, a variant of the watershed transformation, the stochastic watershed, is applied to extract the vascular skeleton.

Notwithstanding most of the state-of-the-art methods look for detecting all vessel pixels [1], there are also some attempts focused on finding the vessel skeleton, or in other words, the vessel centerline. The work of Chen et al. is based on shortest path connection [2], Sofka and Stewart on the use of matched filters [3], Wu and Derwent on ridge descriptors [4] and Walter and Klein and Bessaid et al. on the application of watershed transformation [5, 6] but none of them is based on the use of stochastic watershed.

The rest of the paper is organised as follows: in Section 2 the main stages of the proposed method are described, detailing the morphological operators used, the stochastic watershed transformation and the centerline detection algorithm. Section 3 shows the experimental results obtained on images belonging to two public databases, and a comparison with other methods from the literature. Finally, Section 4 provides conclusions and some future work lines.

2. METHOD

2.1. Morphological operators

Mathematical morphology is a non-linear image processing methodology, based on minimum and maximum operations,

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which can be used to extract relevant structures of an image f [7]. 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 applies these basic filters directly, or uses them to derive more complex operators, such as a *dual top-hat* ($\rho_B(f) = \varphi_B(f) - f$) or geodesic transformations. The *geodesic dilation* is the iterative unitary dilation of an image f (marker) which is contained within an image g (reference), $\delta_g^{(n)}(f) = \delta_g^{(1)}\delta_g^{(n-1)}(f)$, being $\delta_g^{(1)}(f) = \delta_B(f) \wedge g$. The *reconstruction by dilation* is the successive geodesic dilation of f regarding g up to idempotence, $\gamma^{rec}(g, f) = \delta_g^{(i)}(f)$, so that $\delta_g^{(i)}(f) = \delta_g^{(i+1)}(f)$. Using the *geodesic reconstruction*, a *close-hole operator* can also be defined. For a grey-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 fills all holes in an image f that do not touch the image boundary f_∂ (used as marker): $\psi^{ch}(f) = [\gamma^{rec}(f^c, f_\partial)]^c$, where f^c is the complement image (i.e., the negative).

2.2. Stochastic watershed transformation

Watershed transformation is a segmentation technique for gray-scale images [8]. 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, a watershed transformation variant, is used to solve the sub-segmentation conflict [9]. 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. 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 necessary to perform a last marker-controlled watershed on the *pdf* obtained to obtain a final result. This type of watershed works better than other marker-based watershed transformations used previously in the literature.

2.3. Algorithm

This paper is focused on obtaining directly the skeleton of the retinal vascular tree instead of obtaining it after a complete segmentation of retinal vessels. As mentioned above, the proposed method is mainly based on mathematical morphology along with curvature evaluation. Its main stages are included in the flowchart shown in Fig. 1 and can be also observed in the images of Fig. 2.

Although fundus images are RGB format (Fig. 2a), the present work is drawn on monochrome images obtained from the green component extraction because this band provides improved visibility of the blood vessels (Fig. 2b). Moreover, the intensity of this image is adjusted such that 1% of data is saturated at low and high intensities. Then, a small opening, using a disc of radius 1 as SE (B_1), is performed on the enhanced green component image to fill in any gaps in vessels that could provoke subsequent errors, for example due to brighter zone within arteries. Next, a dual top-hat, with a SE larger than the widest vessel (B_2), is applied with the goal of extracting all of them and eliminating structures with high gradient that are not vessels, as occurs in the optic disc (Fig. 2c). Afterwards, with the aim of highlighting the vessels on the background, principal curvature, f_κ, is calculated as the maximum eigenvalue of the Hessian matrix [10] resulting the image shown in Fig. 2d. Finally, stochastic watershed is applied to the curvature image.

This transformation uses random markers to build a probability density function (*pdf*) of contours (Fig. 2e), which is then segmented by a last volumetric watershed. Thereby, the vascular skeleton is part of the frontiers of the resultant regions (Fig. 2f). In addition to the random markers some controlled markers are also included. It is forced that there is at least one marker in the area delimited by the crossing of two vessels. These areas are determined by means of the residue of the close-hole operator on f_κ. This methodology avoids that some vessels are not detected by the watershed transformation (see Fig. 3).

In order to discriminate which frontiers are significant and which ones are not and should be filtered out, the frontiers are multiplied by f_κ (Fig. 2g) and then are thresholded (Fig. 2h) using a fixed threshold, experimentally $t = 0.05$. Once the skeleton is obtained, a pruning process is applied to remove possible spurs giving rise to the final result of the presented method (Fig. 2i and 2j). The implemented pruning process is

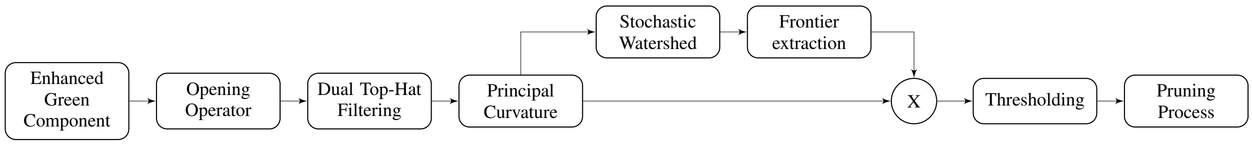


Fig. 1. Flowchart for skeleton extraction.

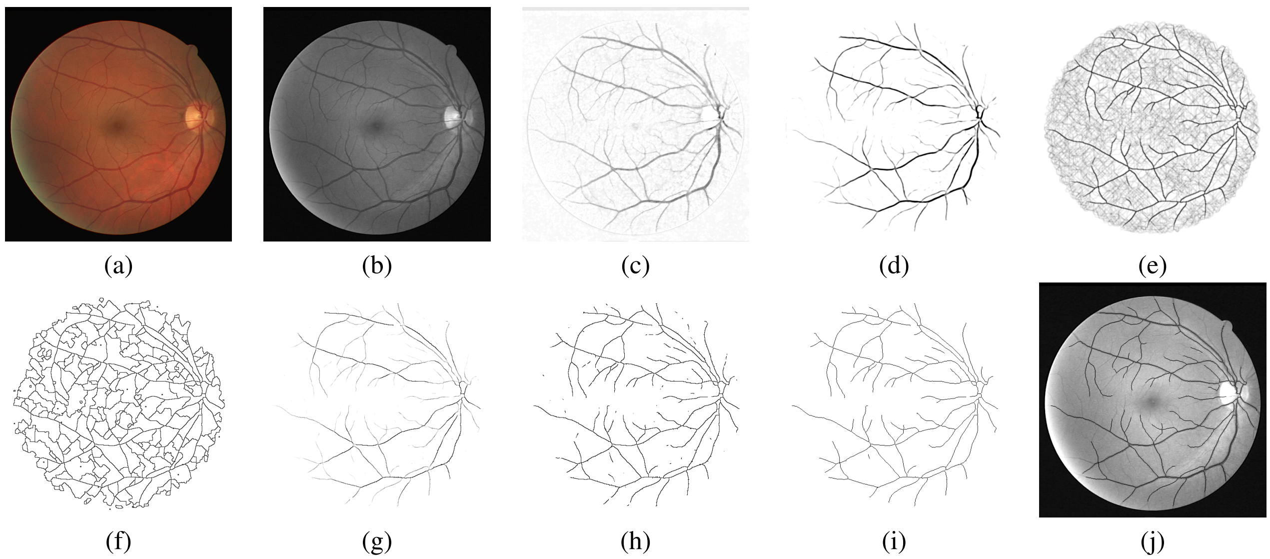


Fig. 2. Skeleton extraction process: (a) Original fundus image, (b) Green component, (c) Dual top-hat filtering, (d) Principal curvature, (e) Probability density function (pdf) of contours obtained with 10 simulations and 300 random markers, (f) Watershed frontiers, (g) Product between the principal curvature and the watershed frontiers, (h) Thresholding ($t = 0.05$), (i) Pruning and (j) Final result. The images (c)-(i) have been inverted for better visualization.

characterized by removing spur branches but without altering the main branches. Only the branches whose size is less than a threshold are removed while the other are left intact.

Next algorithm summarizes the steps of the vessel centerline extraction method that has been explained.

Algorithm: Vessel centerline extraction

Data: Original RGB fundus image $\mathbf{f} = (f_R, f_G, f_B)$
Result: Vessel centerline, f_{out}

initialization: B_1, B_2 ;
$f_{in} \leftarrow f_G$ Green component selection ;
$f_{enh} \leftarrow \Gamma(f_{in})$ Image Intensity Adjustment ;
$f_{op} \leftarrow \gamma_{B_1}(f_{enh})$ Opening ;
$f_{dth} \leftarrow \rho_{B_2}(f_{op})$ Dual top-hat ;
$f_\kappa \leftarrow max[eig(H(f_{dth}))]$ Principal curvature ;
$f_{ws} \leftarrow WS(f_\kappa)_{f_{mrk}}$ Stochastic Watershed ;
$f_{th} \leftarrow (f_\kappa \times f_{ws}) < t$ Thresholding ;
$f_{out} \leftarrow \Upsilon(f_{th})$ Pruning ;

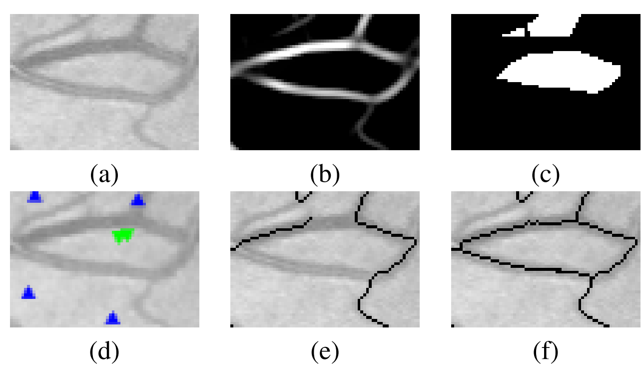
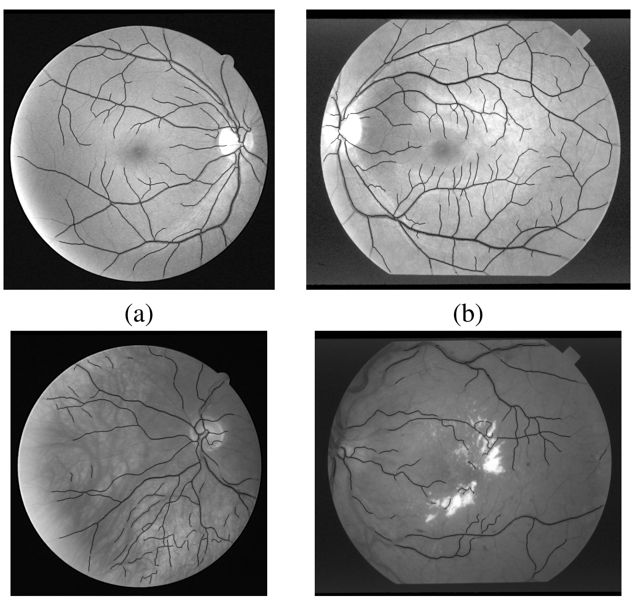


Fig. 3. Stochastic watershed on the crossing of two vessels: (a) Enhanced green component, (b) Principal curvature (f_κ), (c) Residue of close-hole operator, (d) Random (blue ▲) and controlled (green ▼) markers, (e) Result of the stochastic watershed using only the random markers shown in blue and (f) Result of the stochastic watershed combining random and controlled markers (blue and green).

3. RESULTS

The validation of the method has been carried out on 2 public databases widely used: DRIVE [11] and STARE [12]. DRIVE database contains 40 retinal images of 565 x 584 pixels, 33 do not show any sign of diabetic retinopathy and 7 show signs of mild early diabetic retinopathy. The set of 40 images is divided into a training and a test set. For the training images, a single manual vessel segmentation is available but for the test cases two manual segmentations are included. STARE database is a set of 20 images along with two hand labelled vessel network provided by different experts.

Although, in both databases, manual segmentations are included, these segmentations correspond to the complete vasculature not to the vessel centerline which is the goal of this work. For that reason, the homotopic skeleton [7] associated to the hand segmentations was obtained for future comparisons. In Fig. 4, the results on some images from DRIVE and STARE databases can be observed.



(a) (b) (c) (d)

Fig. 4. Skeleton results of the proposed method: (a,c) DRIVE images ('19_test' and '23_training') and (b,d) STARE images ('im0255' and 'im0001').

The validation has been performed in two ways. One of them is based on comparing the results of this work with methods that first segment the vessels and after perform a skeletization process and the other compares it with algorithms that obtain the skeleton directly.

On the one hand, regarding methods that require a previous segmentation, the presented algorithm has been compared with two methods published previously. The local maxima over scales of the magnitude of the gradient and the maximum principal curvature of the Hessian tensor are used in a multiple pass region growing procedure in the first work [10]. The other method [13], as this work, is based on mathematical morphology and curvature evaluation although the morphological operations used are different as well as the obtained result. In the same way as explained above, the homotopic skeleton was performed after the segmentation process in both cases. On the other hand, as for the methods that obtain directly the retinal vessel centreline, the analysis has been focused on other two approaches based also on watershed transformation [5, 6]. In Figure 5, the strengths and weaknesses of the proposed method can be observed in two examples of both databases.

4. CONCLUSIONS

A method to determine the vascular skeleton on a fundus image has been presented. This work proposes a new approach based on mathematical morphology and curvature evaluation and makes use of the stochastic watershed to extract the vessel centerline in a direct way. A correct vessel skeleton detection is usually required to analyse different vessel features that can indicate the presence of several diseases.

Avoiding complete vessel segmentation supposes an improvement in the automatic fundus processing since the skeleton is not dependent of a previous stage and the computational cost is reduced by decreasing the number of required steps. Apart from this fact, it must be stressed that an important advantage of the proposed method is its performance in pathological images or with large changes in illumination, as was observed in Fig. 4 and 5. In those cases, the algorithm presented in this paper works properly and reduces over-segmentation problems which can be found in methods based on a previous segmentation as [10, 13]. With regard to other methods that obtain the skeleton in a direct way and use the watershed transformation [5,6] instead of the stochastic watershed, the proposed work achieves a more robust detection and decreases the number of spurs. Despite good results, it must be mentioned that the main disadvantage of the method is that some vessels can lose their continuity if some part of them are not detected and it should be corrected in a post-processing stage.

About future work lines, some post-processing could be applied on the disconnected skeleton branches to join them if it was necessary and a wider validation of the method could be performed.

REFERENCES

[1] M.M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A.R. Rudnicka, C.G. Owen, and S.A. Barman, "Blood vessel segmentation methodologies in retinal images a survey," *Computer Methods and Programs in Biomedicine*, vol. 108, no. 1, pp. 407 – 433, 2012.

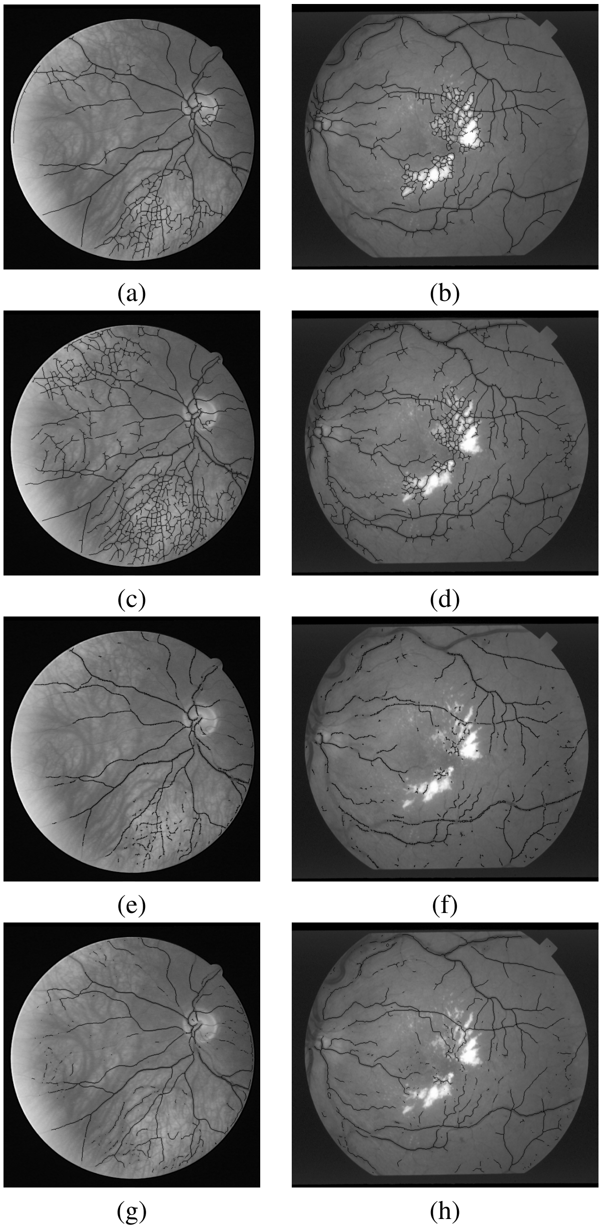


Fig. 5. Comparison between different methods: (a,b) Martinez et al. method [10], (c,d) Morales et al. method [13], (e,f) Bessaid et al. method [6] and (g,h) Walter and Klein method [5]. First column: DRIVE image '23_training' and second column: STARE image 'im0001'. These images must be compared with the result of the proposed work shown in images c and d of Fig. 4.

[2] L. Chen, Y. Ju, S. Ding, and X. Liu, "Topological vascular tree segmentation for retinal images using shortest path connection," in *Image Processing (ICIP), 2011 18th IEEE International Conference on*, Sept 2011, pp. 2137–2140.

[3] M. Sofka and C.V. Stewart, "Retinal vessel centerline extraction using multiscale matched filters, confidence and edge measures," *IEEE TMI*, vol. 25, pp. 1531–1546, 2006.

[4] C. Wu, J.J. Kang Derwent, and P. Stanchev, "Retinal vessel radius estimation and a vessel center line segmentation method based on ridge descriptors," *Journal of Signal Processing Systems*, vol. 55, no. 1-3, pp. 91–102, 2009.

[5] T. Walter and J.C. Klein, "A computational approach to diagnosis of diabetic retinopathy," *6th Conference on Systemics, Cybernetics and Informatics (SCI)*, 2002.

[6] A. Bessaid, A. Feroui, and M. Messadi, "Detection of blood vessels from retinal images using watershed transformation," *Journal of Mechanics in Medicine and Biology*, vol. 09, no. 04, pp. 633–642, 2009.

[7] P. Soille, *Morphological Image Analysis: Principles and Applications*, Springer-Verlag New York, Inc., 2nd edition, 2003.

[8] S. Beucher and F. Meyer, *The Morphological Approach to Segmentation : The Watershed Transformation*, chapter 12, pp. 433–481, E. Dougherty Ed., 1992.

[9] J. Angulo and D. Jeulin, "Stochastic watershed segmentation," in *Proc. of the 8th International Symposium on MathematicalMorphology (ISMM'2007)*, 2007, pp. 265–279.

[10] M.E. Martinez-Perez, A.D. Hughes, S.A. Thom, A.A. Bharath, and K.H. Parker, "Segmentation of blood vessels from red-free and fluorescein retinal images," *Medical Image Analysis*, vol. 11, no. 1, pp. 47 – 61, 2007.

[11] J. Staal, M.D. Abramoff, M. Niemeijer, M.A. Viergever, and B. van Ginneken, "Ridge-based vessel segmentation in color images of the retina," *Medical Imaging, IEEE Transactions on*, vol. 23, no. 4, pp. 501 –509, april 2004.

[12] A. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," *IEEE Transactions on Medical Imaging*, vol. 19, pp. 203–210, 2000.

[13] S. Morales, V. Naranjo, J. Angulo, J.J. Fuertes, and M. Alca niz, "Segmentation and analysis of retinal vascular tree from fundus images processing," in *International Conference on Bio-inspired Systems and Signal Processing (BIOSIGNALS 2012)*, 2012, pp. 321 – 324.