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Comparison of Various Methods to Delineate Blood Vessels in Retinal Images

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Introduction

The blood vessels in the human retina are easily visualisable via digital fundus photography and provide an excellent window to the health of a patient affected by diseases of blood circulation such as diabetes. Diabetic retinopathy is identifiable through lesions of the vessels such as narrowing of the arteriole walls, beading of venules into sausage like structures and new vessel growth as an attempt to reperfuse ischaemic regions. Automated quantification of these lesions would be beneficial to diabetes research and to clinical practice, particularly for eye-screening programmes for the detection of eye-disease amongst diabetic persons.

We compare a number of methods to detect and delineate blood vessels in retinal images including an approach using Wavelets developed by ourselves [5], and a number of other approaches reported in the literature [2, 4, 6, 8]. Previous studies have tended to work with fluorescein angiographic images in which blood vessels are well highlighted, however this procedure carries health risks which limits its usability. We are therefore particularly interested in analysis of non-mydriatic colour retinal images as obtained by standard eye-screening programmes. The vessel detection methods are tested on the publicly available STARE database of retinal images [3], which comprises 20 retinal images, and gold-standard images consisting of the delineated blood vessels as determined by two ophthalmologists. A testing methodology, inspired by the free-response receiver operator characteristic (FROC) analysis [1], is employed to evaluate the efficacy of the vessel detection methods.

In the following we give a brief description of each vessel detection method and our implementation of it. The testing methodology is outlined and the results presented.

Theory

Blood vessels in retinal images are well distinguished in the green field of a RGB image, and we use that for processing. The vessels are continuous, with little curvature branching out in a tree-like structure. Their cross-sectional intensity profile can be usefully modelled as a Gaussian function. The diameter of the vessels changes only slowly as one traverses along the vessels and is in the range of 4–20 pixels for images of the resolution of the STARE database (705 × 600 pixels for a 50° field-of-view of the retina). The methods we describe for detecting

blood vessels are based upon, at least in part, on the above observations. The description of the methods follows.

Wavelet Transform

The 2D continuous wavelet transform (CWT) is used to detect vessels with the Morlet as the mother wavelet [5] by varying parameters of scale and rotation angle. The Morlet wavelet is chosen because it is directional (in the sense of being effective in selecting orientations) and capable of fine tuning specific frequencies. This latter capability is especially important in filtering out the background noise. These characteristics of the Morlet wavelet represent its advantages with respect to other standard filters such as the Gaussian and its derivatives. Its parameters are chosen to make the filter elongated and a low frequency with few significant oscillations is set for the wavelet's complex exponential. The transform maximum response (in modulus) calculated from a set of orientations for each position is then taken, emphasising the blood vessels in all directions and filtering out most of the noise.

The segmentation is produced by classifying each pixel as belonging to the class of vessel or non-vessel pixels, based on each their features. The classification is supervised and the training set is obtained from a hand-drawn labelling of a region of the image to be segmented. The pixels' feature space was formed by maximum modulus Morlet wavelet responses (taken at different scales and elongations), gaussian gradient responses at different scales, mean filter responses and also colour information (namely, the red, green and blue channels). A feature extraction process was used to obtain a lower dimensional feature space, whilst preserving the structure important for classification.

Matched-filtering

One of the earliest described approaches to detecting blood vessels used matched-filtering to isolate long linear structures in the image with a cross-section of a Gaussian [2]. A kernel, of size 11×11 pixels, with a Gaussian profile in one direction and a constant profile in the orthogonal direction, is correlated with the image at each point to give an estimate of likeness of a local region to a vessel. The kernel is rotated at $15°$ increments and correlated with the image thereby picking out vessels at various orientations. The maximal response over all orientations is retained at each pixel and the results is thresholded with a global threshold to give a vessel pattern. We apply a final morphological filtering, not described in the inital paper, to remove noise pixels.

Morphological Tophat and Curvature Estimation

As Vincent described [7] the vessels in a retinal image can be segmented by applying a morphological opening with a long linear structure of 1 pixel width at various orientations. The result can be improved by following up the opening with a morphological reconstruction which reduces the smoothing effect of the opening. This approach is not specific enough in that any bright structure in the image that the structuring element can fit into is segmented. Large objects in addition to vessels can satisfy this condition. Zana and Klein [8] describe further filtering with morphological operators to refine the process to be more specific to

vessels. This produces an image where the intensity of the pixel relates to the likelihood of that pixel being vessel. We threshold this image to obtain a vessel detection result. In addition, we threshold the reconstructed opened image (at the mid stage of processing) to obtain an alternative vessel detection. As reported in Results below, it is the threshold of the mid-stage of processing that we find to have the better result!

Curvature Estimation by the Hessian Matrix

Martinez-Perez [6] point out that if the second partial derivatives are calculated on the mathematical model of the vessel intensity profile (Gaussian in one direction, constant linear in the other) then the derivative in the direction of the vessel cross-section will have a low negative value in the central region of the vessel. They therefore calculate the second-partial derivatives ($f_{xx}, f_{xy} = f_{yx}, f_{yy}$) at each pixel in the image, form the Hessian matrix, and find the smallest eigenvalue. This in effect is a rotation of the calculation of the partial derivatives to give the derivative in the direction across the vessel profile. The smallest eigenvalue is the estimate of this derivative and should be smaller than other parts of the image based on the Gaussian profile model of the vessel. By thresholding the image formed by the smallest eigenvalue at each point an vessel pattern image is arrived at. Martinez-Perez *et al.* describe a further region growing procedure to inforce connectivity constraints on the detected vessels. We have not implemented that further refinement of the algorithm.

Multi-threshold Probing

A very different approach is described by Jiang and Mohon [4]. They threshold the original retinal image at a fixed threshold. This provides an image that has part of the vessel network reasonably well detected, with a lot of other extraneous noise detected in other parts of the image. They apply a series of tests to each pixel. Each pixel must be within a small distance of the background (because vessel pixels are never far away from the edge of the vessel) and have suitable contrast compared to nearby background pixels. Objects that are left after this are then tested for size: objects too small are eliminated. This procedure provides a part of the vessel network. To obtain the full vessel network, the original retinal image is thresholded at a number of other thresholds and the pruning operations are applied to retain only vessel pixels. Combining the results of these operations provides the full network.

Testing Methodology

Three of the vessel detection methods terminate with a global threshold. The value of the threshold can be adjusted to make the detection more sensitive or more specific. The vessel detection results are compared to the gold-standard images of one ophthalmologist. Detected pixels corresponding to a pixel in the gold-standard marked as vessel are counted as true-positives, and detected pixels corresponding to unmarked pixels in the gold-standard are counted as false-positives. The counting of pixels in this manner is only carried out within a region of the image comprising the camera aperture. The true-positive fraction is the number of true-positives detected divided by the number of pixels marked as vessel in the gold-standard. The false-positive fraction is the number of false-positives divided by the number of pixels in the gold-standard not marked as vessel. Results are averaged over the twenty images of the Stare database. The Wavelet method incurs some edge effects that result

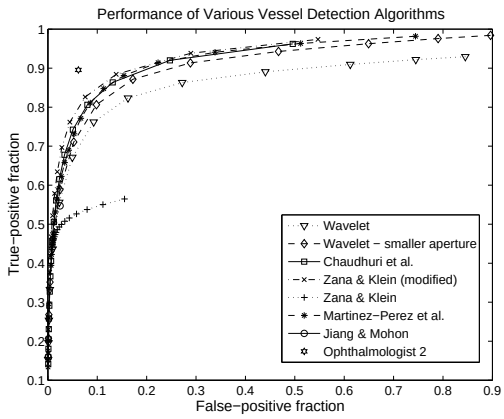

Figure 1: Results of the vessel detection of five methods

in degraded detection ability at the edges of the processed area. We also present results for the Wavelet transform that used a slightly reduced aperture to eliminate these edge effects.

Results

The results of the five methods for detecting blood vessels in non-mydriatic colour fundus images of the Stare database are shown in figure 1. The sensitivity of four methods are able to be adjusted and these appear in the graph as curves tracing out an arc of true-positive fraction versus false-positive fraction. The method due to Jiang and Mohon was not easily able to be adjusted to different sensitivity and was only operated for one set of parameters. It appears as a point in the graph. The second set of gold-standard images as determined by a second ophthalmologist was tested against the first gold-standard. This also appears as a point in the graph.

Discussion

Unfortunately this multi-detection problem violates the Poisson assumption linking FROC analysis to ROC analysis (see [1]). The statistical model of FROC analysis cannot be usefully applied and there is no known method to estimate the confidence intervals of the result curves. We can only conclude that the majority of methods detect vessels to a similar ability, despite their disparate approaches to segmentation, to the level which this study can distinguish detection characteristics. There is one exception, and that is the morphological and curvature estimation of Zana and Klein [8], which in our implementation performed poorly compared to stopping the process at an earlier stage.

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