Blood vessel tracking in retinal images

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Abstract

This paper investigates the image processing techniques to identify blood vessels in the retinal images. Each identified vessel is stored and labelled with a number which also indicating whether the vessel originates from the optic disc or it is a branch of a vessel which originates from the optic disc. Non-linear fitting technique is used to process each point on blood vessels locally. The algorithm described in this paper is intended to process a large amount of retinal images preserved by the Canterbury District Health Board.

Keywords: retina, blood vessel, tracking

1 Introduction

The leading cause of blindness in working age people is due to diabetic complications\(^1\). Diabetes affects the vascular system, and the potential consequence of this for the eye is progressive death of the retina due to the loss of the blood supply. The resulting visual loss brings significant costs, both to the individual and to society. Early ophthalmic intervention and constant monitoring is essential, with an estimated 90% of visual loss being avoidable if followed\(^2\).

Monitoring takes the form of regular retinal examinations; digital images of the retina are taken and graded by trained professionals. The progression of diabetic retinopathy is assessed for its level of severity, which in turn determines the frequency of examinations. The Canterbury District Health Board (CDHB) operates such a scheme. However a significant shortage of professionals to read the images in New Zealand and internationally, has lead to a research programme at the CDHB looking at some form of computer assisted screening. The work described in this paper is part of this research programme.

This paper describes work looking at the detection and tracking of blood vessel. This can, in turn, be used for the detection of microaneurysms, registration of images over time to map changes, and the detection of other pathologies. The images used for developing the blood vessel tracking technique are provided by CDHB. Their database consists of some 100,000 plus images\(^3\). A subsample of high quality images were chosen for this work, as the quality of those images may have a significant degree of influence on the performance of the technique. An automated system for determining image quality is the focus of a separate research project.

This paper is based on the earlier work of Huang\(^4\), with the aim of making significant improvements to this technique. In section 2 we outline the basis of his blood tracking algorithm, while in section 3 we present the modifications needed to deal with vessel branching. The results are presented and discussed in section 4. Finally, a conclusion and related future work is given in section 5.

2 Blood vessel tracking

The goal of blood vessel tracking is to find and store all vessels, and each vessel will be labelled with a number.

The blood vessel tracking process includes the following steps: detecting optic disc, locating starting points, building up a Gaussian model which describes the cross section of a blood vessel, and tracking the blood vessel from the starting points using non-linear least squares fitting.

2.1 Optic disk detection

Here we simply follow the technique of Huang\(^4\). Consider the sample image shown in Figure 1(a).

We begin our search for the optic disc by extracting a large subimage around the brightest point in the image, Figure 1(b), as this brightest point is normally within the disc. A morphological closing procedure is used to blur the blood vessels in the subimage leaving only the optic disc edge for detection, as shown in Figure 1(c). Figure 1(d) shows...
Figure 1: Optic disc detection. (a) The green plane of a retinal image, (b) the local area of the optic disc, (c) the optic disc after blood vessel removal, (d) Canny edge detection of the disc.

Figure 2: Locating the starting points for blood vessel tracking. (a) An intensity profile circle centred on the optic disc is shown, (b) a one-dimensional plot of the intensity profile (blue) and threshold (red), (c) located starting points on the profile circle.
the result of Canny edge detection for locating the disc edge. The centre and radius of the optic disc are then calculated from three points located on the detected edge.

2.2 Starting point location

A circle centred at the centre of the optic disk, with a radius two time of that of the optic disc, is drawn, as shown in Figure 2(a). The pixels on this circle are extracted as intensity profile and a threshold is determined based on the running average and variance, Figure 2(b). Any pixel in the intensity profile which has an intensity value below the threshold is considered to be in a blood vessel. Figure 2(c) shows the located starting points.

2.3 Modelling a vessel

A Gaussian model is then built up to model the cross section profile of a blood vessel [4]. Figure 3 shows such a model. The model is described by,

\[ I = A - B e^{-(v-u_0)^2/2\sigma^2} \]  

(1)

where \( A \) is the average background intensity, \( B \) is the contrast of the vessel with respect to the background, \( \sigma \) is the width of the vessel, and \( u_0 \) the offset[4].

2.4 Blood vessel tracking

Tracking begins with the located starting, together with initial estimates for the Gaussian model coefficients. The algorithm compares the model to a cross-sectional intensity profile through the image, local to each candidate vessel point, from this a new set of model coefficients are computed. In practice the cross-sections are two-dimensional to improve the accuracy of the estimate. The algorithm then steps to the next candidate point based on the estimated orientation and width of the blood vessel. This process is carried out iteratively until some ending criterion is met. The algorithm can be summarised by the steps,

1. At the starting points, extract a set of coefficients including: background intensity \( A \), contrast of vessel \( B \) with respect to the background, the offset \( u_0 \) and the width of the vessel \( \sigma \) and the orientation angle of the vessel at the starting point \( \theta \).

2. Compare the model (described by the set of coefficient obtained in step 1) with the cross-sectional profile of the point which is currently being processed and obtain a new set of coefficients, which best describe the cross-sectional profile.

3. Step to the next point by moving a distance of \( 2\sigma \) in the direction of \( \theta \).

4. Check this point against ending criterion, if the criterion is not met, go back to step 2.

The ending criterion is determined as,

1. One of the computed coefficients significantly deviates from its normal value.

2. The estimated next candidate location is too close to the currently processed candidate (insufficient progress is being made).

3. The estimated next candidate location is outside the image boundary.

The algorithm described above tracks along vessels from their starting points. For each starting point there will be one vessel tracked. Figure 4 shows one such branch that has been processed. Invariable the tracking terminates at the junction of a vessel branch as the model breaks down at these points.
Figure 5: Restarting the blood vessel tracking process on vessel branches. (a) An intensity profile circle centred on a candidate branch point, (b) a one-dimensional plot of the intensity profile (blue) and threshold (red), (c) successful tracking of the vessel branches.

Figure 6: Fully processed retinal images tracking blood vessels. (a) Based on Huangs[4] original algorithm, (b) Based on the extended model to track over branches.

Figure 7: Failure of the blood vessel tracking algorithm. (a) Unable to find suitable staring point, (b) false starting points located due to poor image contrast.
3 Improved vessel tracking

Huangs’ algorithm has, unfortunately, a significant short coming in that the model breaks down in the location of vessel branches. Figure 6(a) shows an image processed using this algorithm. The number of vessels equals the number of starting points located. However, across these significant features and including branches is something wish to be able to do.

Since branching could happen anywhere along a vessel, a process of detecting branching is needed to be done at every step as the algorithm moves along the vessel. This branching detection process is similar to the one that finds the starting point. It involves the following steps,

1. Consider a circle of a small radius, 18 pixels, around a tracked point.
2. Extracting the intensity profile of the pixels on this circle.
3. Determining the new starting point from the intensity profile.

In our modified algorithm all tracked points are stored in an array. Each of these points in the array serves as a centre on which a small circle is drawn, as shown in Figure 5(a). Then the intensity profile of this circle is extracted, Figure 5(b).

In the example shown, it is clear that the intensity profile has three points on the circle corresponding to candidate blood vessel locations. However, two of these are in a vessel that is already tracked and need to be discarded. These three points are checked against all points that are stored previously, such that any of these three points which is too close to a stored point is discarded. We are then left only with the one which is on the branch. Now, starting from this starting point the standard non-linear fitting procedure can be carried out to track this branch. Figure 5(c) shows the same vessel as in Figure 5(a) with the branch tracked.

4 Results

Figure 6 shows a fully processed image, with all the blood vessels detected, tracked and labelled.

In Figure 7(a) the upper right hand quadrant of a processed image is shown. In this case it can be seen that the tracking process has failed. In this due to finding suitable starting points associated with the two main blood vessels in the image.

Regarding the performance of this modified algorithm, there are some points worth noting. The run time processing an image is significantly increased with the modified algorithm, due to the large number of candidate starting points associated with a vessel branch. Some of these secondary candidate starting points are false, being erroneously detected from the thresholding of the intensity profile. This is a noise issue and demonstrates the sensitivity of the algorithm in areas of low localised image contrast, as illustrated in Figure 7(b) where the false candidates are shown as the dots inside white circles.

Unfortunately these false starting points take considerable processing time, within the non-linear fitting algorithm, to estimate parameters for the Gaussian blood vessel profile. The more false starting points detected the longer the run time. One way to reduce the run time is obviously to reduce the number of false starting points being found. A median filter can be used to preprocess the image[5]. The median filter effectively eliminates those isolated pixels which have a lower intensity than their surroundings. However, if the dark area is too big then the median filter is not adequate as the size of the filter must be kept small enough so that it does not reduce the sharpness of the image too greatly.

The primary starting points detection is of crucial importance as failure of detecting a starting point leads to failure of tracking a whole vessel and all its branches, Figure 7(a). Therefore, the criterion for detecting primary starting should be deliberately set low. This allows some false starting points being detected but ensures that few are missed.

5 Conclusion and future work

The technique described in this paper is based on [4] but modified so that it not only finds the blood vessels that originate from a set of primary starting point but also finds all branches off of the primary vessels.

The input images for this algorithm are assumed to have good quality in terms of sharpness, contrast, focus and etc. Provided with good quality images, the algorithm effectively finds and stores most blood vessels. Currently the execution time of the algorithm varies from 30 minutes to 2 hours depending on the complexity of the image. Although optimisation of the algorithm has not yet been performed, various approaches to improving execution performance have often implied a trade-off with vessel detection.

The slowness of the current algorithm is mainly due to the performance of a non-linear fitting function, which estimates the parameters that best describe the cross-section of a vessel. We propose in future work an alternative algorithm which extends
the one-dimensional intensity circle profile about each candidate point to locate the next candidate vessel locations. The backward point will be discarded as illustrated in Figure 8. This algorithm could incorporate the Gaussian model into it as a way of determining the optimal radius size of the search circle. This search radius is currently fixed.

As the algorithm moves further towards the end of a blood vessel, the vessel gradually fades into the background and the chance this intensity profile extraction method fails increases. The original non-linear fitting function could be brought back to continue with the tracking down to the end of the vessel. It is hence important to determine at what stage the non-linear fitting function jumps in. It is reasonable to suggest that we use the non-linear fitting function when the intensity profile extraction method fails to find a point to continue on.

References


