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Vessel Segmentation and Branching Detection using an Adaptive Profile Kalman Filter in Retinal Blood Vessel Structure Analysis

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Abstract. This report presents an improved tracking based method for retinal vessel segmentation that uses blood vessel morphology to adapt the tracking parameters. The method includes branching detection and avoidance methods. A bi-level threshold method, based on local vessel information, is used for segmentation. Tracking is based on Kalman filtering. The results are compared with existing ground truth. It is concluded that ground truth segmentation is not easily comparable.

1 Introduction

Several diseases affect blood vessels in the human body, making blood vessel appearance an important indicator for many diagnoses [1]. The retina is one place in the human body where the network of blood vessels can be viewed directly in vivo and examined for pathological changes [2]. The structure of the blood vessels in the retina can in this way be used in the grading of disease severity [3].

Retinal analysis in done through image collection. At present the analysis of these images can only be made by qualified medical staff, but there is a shortage of personnel to perform such examinations. An automated method to analyze the images from the retina would be a precious tool. There are two types of images that can be collected of the retinal blood vessels: retinal angiograms and retinal fundus images. Fundus images were used in this work because, although having lower contrast, they are captured by a non-invasive technique and hence are preferred by the medical community.

Two strategies have been employed in the past for the automatic detection of the retinal blood vessels [4]: scanning [5, 6, 7] and tracking [4, 8, 9]. Scanning is normally a two-pass operation. First feature points are enhanced, followed by a threshold to obtain a binary image. Chaining centerline midpoints is then used to recognize the vessel structure while excluding isolated points. Tracking is a single-pass operation that starts from a given position and extracts image features, gathering structural information, while proceeding using the continuity properties of the vessel. Scanning methods always provide total image segmentation but result in difficult to extract and normally incomplete structural data. Tracking methods easily gather structural information but require vessel continuity for stable operation, and a selected starting point. Scanning methods are more computationally intensive than tracking based methods [4].

We chose to use a tracking method for its computational efficiency and ease of structural information extraction. Kalman filter [11] based tracking was chosen since it has proven itself to be adequate in this type of application [4, 9, 10].

Retinal structure tracking methods must segment the image into vessel/non-vessel pixels. Three approaches exist: amplitude segmentation [8, 9], template matching [4, 5, 6, 12] and parametric model fitting [10, 15]. Thresholding is always needed, either on the filter response (matching) or on the segmentation level (amplitude segmentation/model fitting).

Tracking methods segment the vessel based on its image intensity transverse section (profile). The profile is normally modeled as deriving from a Gaussian shape, caused by the reflection curve from the outer layer of a cylindrical column. In some vessels, due to light refraction on the column of blood within the vessel's wall, light is reflected to the camera causing a 'dip' at the top of the Gaussian shape [14]. Gao et al. [13] analyzed several models and concluded that the best model for blood vessel profiles in retinal fundus images where the 'dip' effect occurs is the difference of two Gaussian functions.

2 Methods

Based on accepted biological properties the following assumptions have been made concerning the appearance of vessels on retinal fundus images:

Piece-Wise Linear Structure: Piece-wise linear, i.e. small curvature, has been assumed in all previous tracking processes [4, 9, 10]. This assumption enables the setting of an upper limit for the curvature of the vessel, so that we can constrain the Kalman filter to a more stable operation point.

Binary Branching Tree: The binary nature of the vessel branching tree can be easily recognized in retinal images. Thus, there can only be two vessels emanating from a branching point [2].

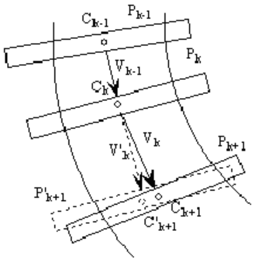
Constant Vessel Width Between Branching Points: The average width variation in inter-branch sections of the vessel can be ignored, in low pathology incidence. Useful in the detection and avoidance of pathologies and crossing, improving the tracking stability.

Used in past literature without proof [8, 9], this property was here verified by observed results. A total of 520 vessel profiles were gathered from linear sections of several different vessels with different widths. The variation of those vessels' width was measured. Using the Kolmogorov-Smirnov statistical the estimate for the average width variation is 0±0.32 pixels with a confidence of 95%.

2.1 Blood Vessel Tracking

The Kalman filter implements a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance in optimal conditions. Though the conditions necessary for optimality rarely exist the filter works well for many applications [16].

The case of Kalman filter tracking of blood vessels deserves special attention since the filter applied to the tracking process is modified so that the calculations become simpler.



P_{k-1} - Previous vessel profile.
P_k - Current vessel profile.
P_{k+1} - Next vessel profile.
P'_{k+1} - Preliminary vessel profile.
C_{k-1} - Previous profile centre point.
C_k - Present profile centre point.
C_{k+1} - Next profile centre point.
C'_{k+1} - Predicted centre point.
V'_k - Predicted direction of tracking.
V_k - Direction of tracking.
V_{k-1} - Previous direction of tracking.

Figure 1: Tracking algorithm schematics.

Fig. 1 shows the spatial schematics for the used Kalman filter. The algorithm uses the previous and current profile's center to predict the vessel's trajectory. Measurement is done and a new profile is obtained giving the correct vessel's trajectory.

$$\hat{px}(k+1) = \phi \times px(k) \qquad (1)$$

$$p = \left[\begin{pmatrix} x \\ vx \\ ax \end{pmatrix}, \begin{pmatrix} y \\ vy \\ ay \end{pmatrix} \right] \qquad (2)$$

$$\phi = \left\{ \begin{array}{ccc} 1 & T & \frac{1}{2}T^2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{array} \right\} \qquad (3)$$

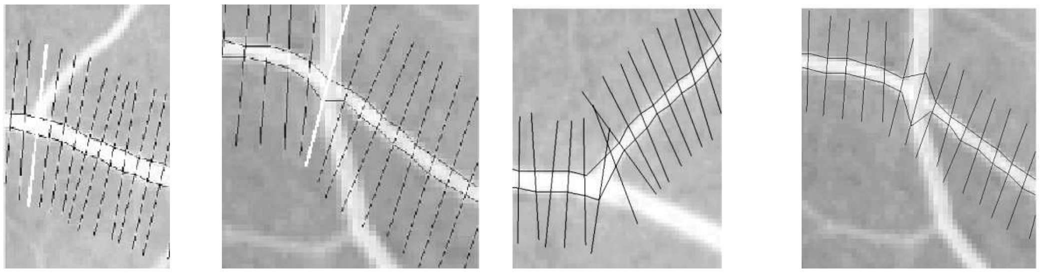
$$px(k+1) = \hat{px}(k+1) + \beta \times P(k) \qquad (4)$$

$$P(k) = \left\{ \begin{array}{c} Z(k) \\ \frac{1}{T}\left(\frac{3}{2}Z(k) - 2Z(k-1) + \frac{1}{2}Z(k-2)\right) \\ \frac{1}{T^2}\left(Z(k) - 2Z(k-1) + Z(k-2)\right) \end{array} \right\} \qquad (5)$$

Equations 1-5 give the applied Kalman filter mathematical structure, where T is the tracking step size, $px(k)$ is the state vector, $\hat{px}(k)$ is the predicted state vector, $Z(k)$ is the measurement from the image, β is the filter mixing gain and k is the current tracking step. In literature the gain β is normally one, giving absolute confidence to the measurements [9, 10]. Some authors try to assess a value depending on the assumed errors in each of the model's variables [4].

$$\beta = \begin{cases} 0, \text{current width variation} > 2 \times \text{standard deviation} \\ 1, \text{current width variation} < 2 \times \text{standard deviation} \end{cases} \qquad (6)$$

We here introduce a novel tracking gain that varies as a function of the vessel's width. Based on the constant width principle introduced in Section 2 we assume that if the width doesn't vary the vessel is being followed correctly and so we keep the gain high. Significant changes in width occur only in branch points, crossings or pathology, in those cases the filter's gain is reduced, thus causing the tracking to follow the predicted path without deviation. Gain variation was implemented according to the rules presented in equation 6.



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

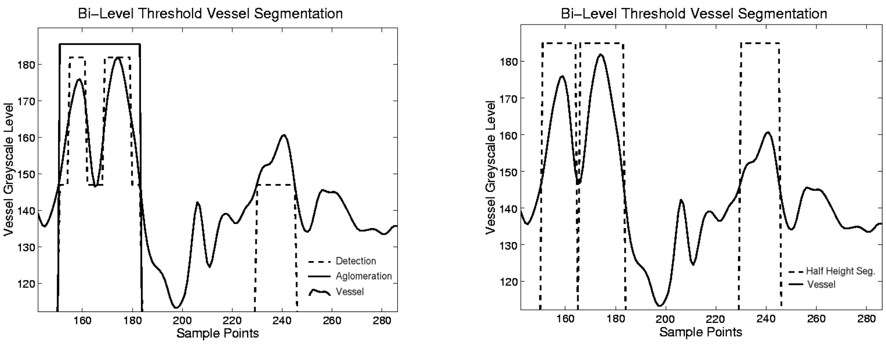
Figure 2: Tracking examples: (a) and (b) show correct tracking resulting from variable gain usage (white line marks the profile where gain was varied), contrary to these results, fixed gain produced the erroneous results in images (c) and (d).

Fig. 2 shows the results from the developed tracking method. Comparing the results in (a) and (b) with (c), respectively, and (d) its is easy to see that fixed gain methods can cause both trajectory (c) and measurement errors (d).

Often, after branching or crossing, several vessels will be detected vessel. The problem of choosing from the several possible vessels is solved based on similarity with the previously tracked vessel. Similarity is measured by euclidian distance in a two dimensional feature space based on width difference and trajectory deviation. The choice is constrained to smaller vessel than the one previously tracked since resulting vessels are always thinner [2]. If no vessel can be found that fits the requirements tracking is terminated and pathology is reported.

2.2 Vessel Segmentation

The objective of this work is the analysis of the retinal vessel structure so an accurate method for vessel segmentation is needed. Matching is known to have low accuracy [12]. Parameterized model techniques presented in [10, 15] were incapable of providing good results in the presence of low contrast or very thin vessels. Single-level direct segmentation [8, 9] was tested using half-height threshold, the results were unsatisfactory since it is more prone to produce sub-division of wider vessel and false positives, as can be seen in Fig. 3 (b).



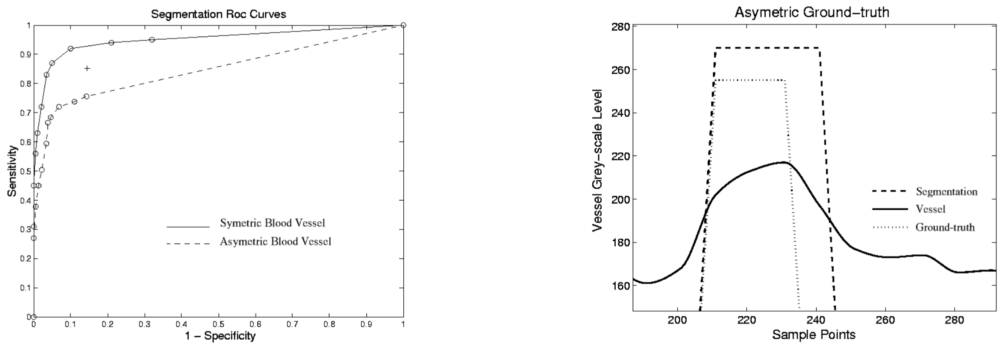
(a) (b)

Figure 3: Bi-Level versus half height segmentation: (a) shows the results from the bi-level thresholding method developed in this work, (b) shows the result from a normal half-height thresholding method as presented in [9].

Here we present a direct segmentation method based on bi-level segmentation with subsequent agglomeration. The values gathered from the previous profiles are used to give the values for thresholding. Information of the last four vessel profiles (if available) is averaged to obtain the maximum (M) and minimum (m) levels used to set the thresholds.Thresholds are set by equation 7.

$$\begin{cases} t1 = m + 0.33 * (M - m) \\ t2 = m + 0.66 * (M - m) \end{cases} \tag{7}$$

Any pixel having intensity above t2 is classified as vessel (condition 1) and all points above t1 that have a neighbor above t2 are also classified vessel (condition 2). This is repeated until there are no more vessel in condition 2. Fig. 3 (a) show the final result of this method.



(a) (b)

Figure 4: Ground-truth comparison results: (a) shows the resulting ROC curves from symmetric and asymmetric ground-truth blood vessels, (b) shows an example of asymmetric ground-truth blood vessel segmentation.

In literature great importance is placed upon the reproduction of ground-truth data [5, 12]. This is logical since we are trying to replace the human interpretation of the retinal images.

It was found that, in existing data [5], ground-truth segmentation levels are asymmetric, as can be observed in Fig. 4 (b). Since the used segmentation method produces a symmetric segmentation, ground truth was impossible to reproduce with the presented method. Fig. 4 (a) shows the ROC curves for a symmetric and asymmetric ground-truth blood vessel respectively. In Fig. 4 (a) the point of operation of a simple half-height segmentation method on a symmetric ground-truth blood vessel is marked by a plus sign.

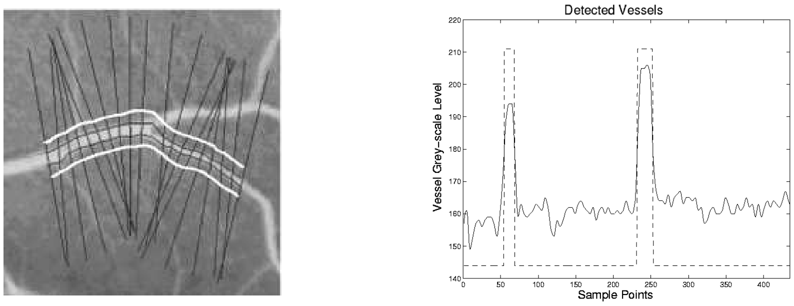
It is believed that the human observer tends to bias its segmentation based on the illumination of the vessel. The flash light used to take the images produces shadow on one of the vessel's side and not in the other due to the spherical geometry of the retina. This makes the ground truth segmentation complex.

2.3 Branching Detection

Most of the tracking methods existing in literature [9, 10] ignore branching of vessels or base detection on the local curvature of the vessel [4]. The first option gives reliable results only during linear sections of the vessel; the second ignores all the small vessels that can branch off the main vessel.

Currently there is no strategy that fully solves this problem: this is because branching is highly irregular and branching rules are not easily gathered from images [2].

Although the tracking method presented here detects branching points which would perturb the tracking so that they can be compensated, there are some vessels that are either too small to perturb the tracking or are missed because they exist between profile samples. To solve the problem we propose the collection of the grey levels in two lines parallel to each side of the vessel, this allows searching for



(a) (b)

Figure 5: Branching Detection Method. (a) shows the tracking of the vessel with two white lines at each side of the vessel, this is where the branching vessels are going to be searched, (b) shows the gathered pixel values and detected vessels in the left side line.

branching vessels using the bi-level threshold used in the main vessel. Fig. 5 shows results of branch detection.

The detected branches can then be used as seed points for the main tracking algorithm.

3 Results

The performance of the variable gain tracker when in presence of branches or crossings was proven to be effective in the available set of images, as can be observed in Fig. 2. This allowed for a better quality in the acquired structural data.

The introduced blood vessel bi-level threshold detection method was found to be more effective than the normally used half-height method [9, 8] as can be seen in Fig. 3 (a). It can be seen that in the presence of symmetric ground-truth this method has higher segmentation quality.

The assumption that blood vessels don't change width between branching points was found to be correct by statistical inference and consequential results.

4 Discussion

The strategy used to develop this algorithm was found to be adequate for retinal blood vessel segmentation. Tracking was shown to allow the integration of local statistical information, effectively allowing for improvement in the tracker efficiency. The variable gain allowed for the avoidance of singularities that otherwise might disturb tracking and corrupt the structural data.

The bi-level threshold technique enabled the correct detection of the vessel even in presence of significant 'dip' effects and nearby smaller vessels.

The proposed method for branching detection gave promising results and is believed to be a good base for a method capable of complete segmentation.

The asymmetry of the ground truth made the reproduction of human segmentation impossible with the presented method. If the proposed dependency of the ground-truth data on illumination is proven, the authors believe that correct segmentation may by possible even in asymmetric cases. However further study is needed.

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