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Retinal Blood Vessel Extraction by using Multi-resolution Matched Filtering and Directional Region Growing Segmentation

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Abstract

A new method to extract retinal blood vessels from a colour fundus image is described. Digital colour fundus images are contrast enhanced in order to obtain sharp edges. The green bands are selected and transformed to correlation coefficient images by using two sets of Gaussian kernel patches of distinct scales of resolution. Blood vessels are then extracted by means of a new algorithm, directional recursive region growing segmentation or D-RRGS. The segmentation results have been compared with clinically-generated ground truth and evaluated in terms of sensitivity and specificity. The results are encouraging and will be used for further application such as blood vessel diameter measurement.

1. Preface

Retinal blood vessels are one of the most important components in ophthalmic diagnosis. As the network of the retinal blood vessels doesn't change very much over time, the location of bifurcation and/or end points can be used as feature points to identify an eye. Detecting abnormalities such as venous looping or beadings is critical for early treatment, as they are, in most cases, indications of potentially sight-threatening retinopathy[1]. In order to utilise these useful characteristics of retinal blood vessels, it is very important to obtain their locations and shapes accurately.

In many of the reported studies on automatic fundus image analysis and diagnosis[2][3][4] normal components within the image, such as blood vessels or fovea, are detected and identified before starting abnormal component detection. Pathologies such micro aneurysms or haemorrhages, located close to blood vessels, may be misclassified as blood vessels and removed in the pre-processing, resulting in reduced specificity of pathology detection and hence possible misdiagnosis. Accurate retinal blood vessel extraction is therefore required as a pre-processing component of an automatic diagnosis/screening system.

In this study, an effective segmentation algorithm for the classification of retinal blood vessels is described. Digital fundus images are colour standardised and contrast enhanced in order to obtain sharp edges in a consistent way. The green bands of the images are then transformed to correlation coefficient images by using two sets of Gaussian kernels. A new algorithm named Directional Recursive Region Growing Segmentation or D-RRGS is applied to the correlation coefficient images to extract blood vessels. The segmentation results are compared with clinically generated vessel segmentations and assessed in terms of sensitivity and specificity of vessel identification. The results are encouraging and will be used in further applications such as blood vessel diameter measurement.

2. Algorithm

Pre-processing

This process includes local contrast enhancement and green band extraction of the digital fundus image. (If necessary, colour standardisation to reduce the variation of retinal colour found in a racially heterogeneous patient sample may be applied.)

The original image is converted from the RGB colour model to HSI. The I band of the resulting image is processed by local contrast enhancement. Local contrast enhancement is a signal to noise enhancement process to create images which are improved for the subsequent retinal blood vessel detection. It emphasises the local contrast of the intensity values of an image so that the blood vessels are more clearly distinguished from the background. It is then converted back to RGB colour model.

From visual observation, blood vessels generally exhibit the greatest contrast from the background in the green band and

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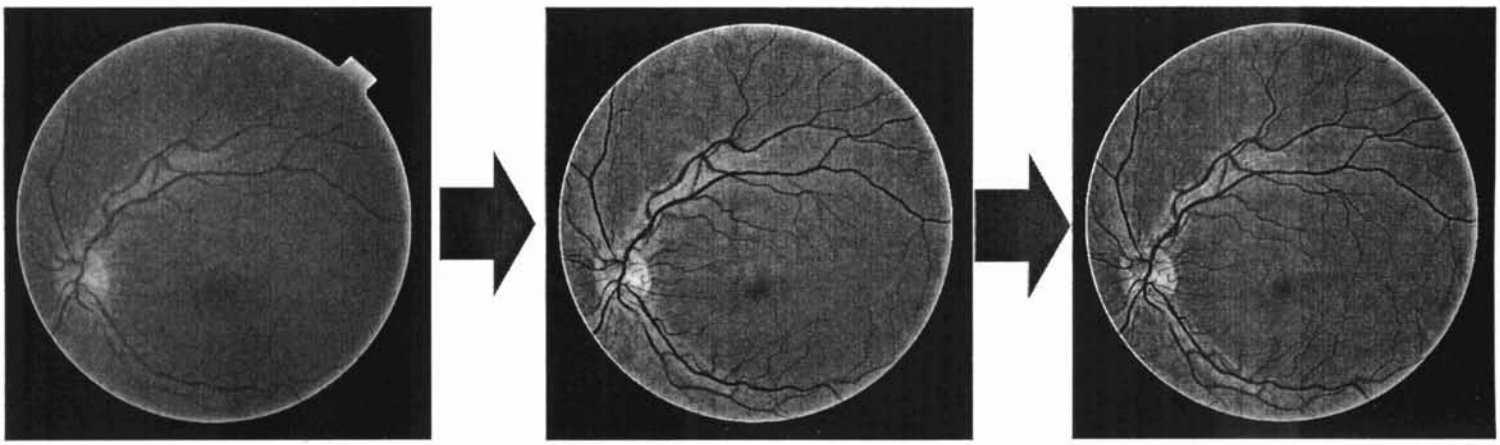


(a) (b) (c)

Fig.2-1: Pre-processing
(a) Original image (multi-band)
(b) Contrast enhanced image (multi-band)
(c) Contrast enhanced image (green band)

therefore the green band is selected from the contrast enhanced images for further processing.

The stages of pre-processing for a typical fundus image are shown in Fig.2-1.

Gaussian kernel patches

In order to cope with a large variety of blood vessel widths, two sets of kernel patches were created; the first set of kernels (set A) is for medium to thick blood vessels and the other set (set B) is for fine vessels. Each set consists of twelve kernel patches of different angle.

The suitable two dimensional kernel K(x,y) may be mathematically described as

$$K(x,y) = -\exp(-x^2/2\sigma^2) \quad \text{for } |y| \le L/2 \quad (2.1)$$

where σ is the variance of the intensity profile, L is the length of the segment for which the blood vessel is assumed to have a fixed orientation. In this study, $\sigma = 2.0$ and L=9 are employed as suggested by Goldbaum et al[5].

Correlation coefficient images creation

The correlation coefficient images used in this paper are created by the following algorithm. Let $I(m,n)$, $P(m,n)$ be the input image and the kernel patch respectively, and WxH, MxN be the size of $I(m,n)$ and $P(m,n)$ respectively, then the correlation coefficient at (x,y) in the input image is given by

$$C(x,y) = \frac{\sum_{j=1}^{M}\sum_{i=1}^{N}\{P(i,j)-\mu_P\}\{I(x+i-M/2,y+j-N/2)-\mu_I\}}{\left[\sum_{j=1}^{M}\sum_{i=1}^{N}\{P(i,j)-\mu_P\}^2\sum_{j=1}^{M}\sum_{i=1}^{N}\{I(x+i-M/2,y+j-N/2)-\mu_I\}^2\right]^{1/2}} \quad (2.2)$$

where

$$\mu_I = \frac{1}{NM}\sum_{j=1}^{M}\sum_{i=1}^{N} I(i,j) \qquad \mu_P = \frac{1}{NM}\sum_{j=1}^{M}\sum_{i=1}^{N} P(i,j) \quad (2.3)$$

$$M/2 \le x \le W\text{-}M/2, \quad N/2 \le y \le H\text{-}N/2 \quad (2.4)$$

The original range of the correlation coefficient is [-1,1], however, it is necessary to convert the range to [0,255] in order to create a 256-tone greyscale image as output.

The conversion is linear and the equation used for the creation of the intensity is

$$Int(x,y) = (c(x,y)+1) \times 127.5 \quad (2.5)$$

$$M/2 \le x \le W\text{-}M/2, \quad N/2 \le y \le H\text{-}N/2 \quad (2.6)$$

where $Int(x,y)$ is the intensity value for the output image and $c(x,y)$ is the correlation coefficient at the coordinate (x,y) where the centre point of the kernel patch matches.

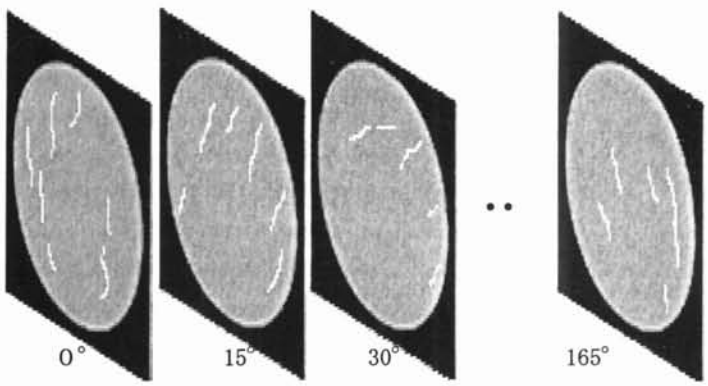


Fig. 2-3: A volume of correlation coefficient images
Sorted in the order of the kernel orientation. They are processed as if the both ends were connected each other.

Fig.2-2 illustrates the creation process of correlation coefficient images. Twelve correlation coefficient

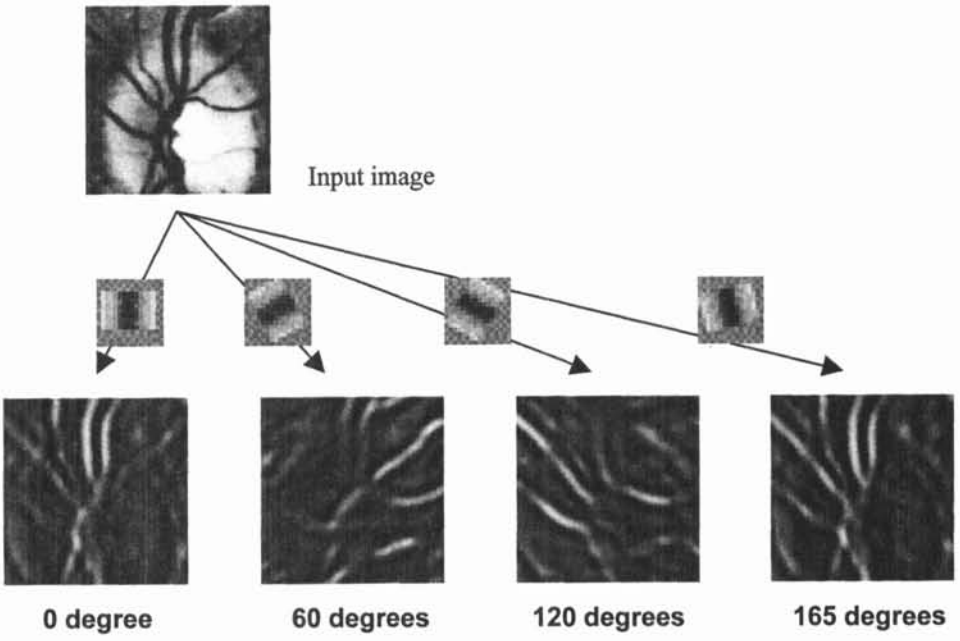


Fig. 2-2: Creation of twelve correlation coefficient images. The original range of correlation coefficient is [-1,1]. The range was converted to [0.255] in order to make greyscale images.

images are generated for each set of the Gaussian kernel patches. As shown in the Fig.2-2, line segments corresponding to the angle of Gaussian bar respond well and, as a result, they have high intensity values.

D-RRGS

The D-RRGS algorithm is applied to the 24 correlation coefficient images. D-RRGS is an enhanced version of region growing segmentation, which has different parameters depending on the direction to grow. The twelve images of each set are considered to be a volume of images closely connected one another. D-RRGS has three directions to grow, that are, parallel to the blood vessels, perpendicular to the blood vessels and perpendicular to image planes (Fig.2-3). The resulting segmented images are all added together into one blood vessel image.

3. Experiment

●Database

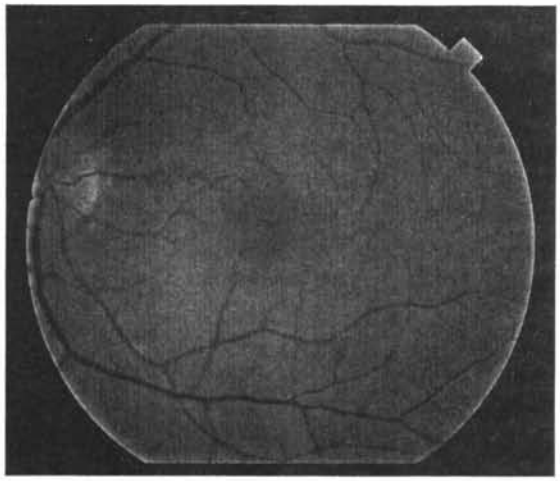
Twenty sets of fundus images and blood vessel ground truth data are used for the performance evaluation. The first 10 sets are images with abnormalities and the rest of the data sets are images without abnormalities. The fundus images and blood vessel ground truth data are obtained from Parallel Architecture Research Laboratory at Clemson university, USA[6].

●Parameter settings

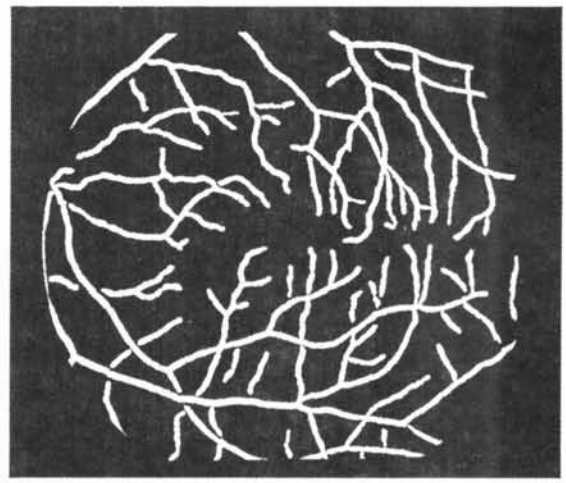
Prior to D-RRGS processing, the correlation coefficient images are rotated in order to reduce calculation complexity. The correlation coefficient image created by θ degrees Gaussian kernel patch will be rotated by $-\theta$ degrees. In other words, each correlation coefficient image is rotated so that the responded blood vessels run along Y-axis on the image. This enables D-RRGS to have only three parameters to control the growing direction, namely, horizontal (H-threshold), vertical (V-threshold) and perpendicular (P-threshold) to the image. In this study, multiple parameter settings are tested. The recognition results created by two of the settings are shown in Table 4-1. The values assigned to H-threshold, V-threshold and P-threshold are 25, 10 and

Table 4-1: Blood vessel recognition rates

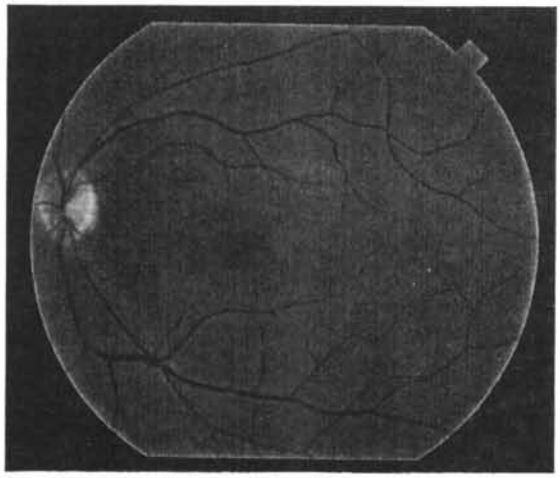
Image#	Set 1(H,V,P)=(25,10,5)		Set 2(H,V,P)=(25,10,0)	
	Sens.(%)	**Spec.(%)**	**Sens. (%)**	**Spec. (%)**
1	78.85	88.42	78.87	90.02
2	79.42	92.18	81.54	93.15
3	82.87	89.76	83.11	90.79
4	71.52	94.47	73.40	94.50
5	81.69	86.41	81.22	87.95
6	84.47	90.00	83.03	90.89
7	86.25	87.57	87.63	88.95
8	88.96	89.46	88.94	90.84
9	84.87	89.50	83.34	90.82
10	83.71	89.38	83.00	89.34
11	86.00	87.48	84.96	90.37
12	85.39	90.33	85.26	91.93
13	77.64	90.68	80.76	91.88
14	79.32	91.53	78.66	92.22
15	78.20	90.81	76.37	92.32
16	76.73	93.17	75.76	93.49
17	86.80	87.05	87.47	90.44
18	76.14	93.87	76.90	94.97
19	81.86	92.82	81.77	93.18
20	72.84	91.08	70.50	91.50
average	**81.18**	**90.30**	**81.12**	**91.48**



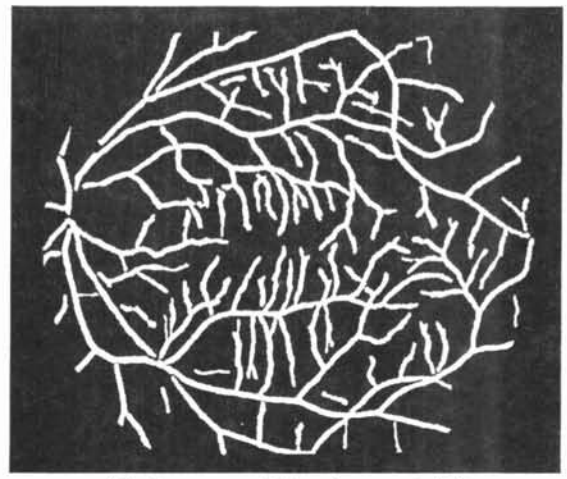
(a) Original fundus image(1)



(b) Extracted blood vessels(1)



(c): Original fundus image(2)



(d) Extracted blood vessels(2)

Fig4-1: Blood vessel extraction results

5 for the first set and 25,10,0 for the second set, respectively.

4. Results

The resulting extracted blood vessels were assessed in terms of sensitivity and specificity using a standard set of hand-labelled segmentation data. The performance achieved is very promising, being sensitivity 81.18% and specificity 90.30% for the parameter set1 and sensitivity 81.12% and specificity 91.48% for the parameter set 2.

5. Conclusion

The proposed algorithm has been shown to be a highly effective method for classifying retinal blood vessels. The accuracy of the extracted blood vessels is such that they contain useful information. In particular they provide the coordinates of bifurcation points and end points, which can be used as feature points for fundus image mosaicing and registration[6].

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