SEGMENTATION OF RETINAL BLOOD VESSELS USING SCALE-SPACE FEATURES AND *K*-NEAREST NEIGHBOUR CLASSIFIER

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ABSTRACT

In this paper, a new feature vector for each pixel, in conjunction with the *K*-nearest neighbour classifier, is proposed for the segmentation of retinal blood vessels in digital colour fundus images. The proposed feature vector consists of two scale-space features - the largest eigenvalue and the gradient magnitude - of the intensity image, representing the two attributes of any vessel, i.e. the piecewise linearity and parallel edges, as well as the green channel image intensity. In terms of sensitivity and specificity, our results are comparable with other supervised method which uses a set of 31 features, yet in terms of processing time, our method uses a smaller number of features and results in a significant reduction in the processing time.

1. INTRODUCTION

Automatic segmentation of blood vessels in retinal images is very important in early detection and diagnosis of many eye diseases. It is an important step in screening programs for early detection of diabetic retinopathy [1], registration of retinal images for treatment evaluation [2] (to follow the evaluation of some lesions over time or to compare images obtained under different conditions), generating retinal map for diagnosis and treatment of age-related macular degeneration [3], or locating the optic disc and the fovea [4].

Methods for blood vessels segmentation of retinal images, according to the classification method, are divided into two groups, supervised and unsupervised methods. Unsupervised methods in the literature comprises the matched filter responses, edge detectors, grouping of edge pixels, model based locally adaptive thresholding, vessel tracking, topology adaptive snakes, and morphology-based techniques [5]. Supervised methods, which required manually labelled images for training, are the recent approaches in vessel segmentation and use the neural networks [1], or the *K*-nearest neighbour classifier [5, 6] for classifying image pixels as blood vessel or non-blood vessel pixels.

Scale-space features such as the gradient magnitude of the image intensity and the ridge strength, both at different scales, are combined with region growing to segment the blood vessels from red-free and fluorescein clinical retinal images [7]. Also, the $1st$ and $2nd$ derivatives - of the green channel image, in x and y directions [6], or with respect to other image coordinates [5] at different scales - are used as features for every pixel in the retinal images. Because taking derivatives of discrete images is an ill-posed operation, these are taken at a scale s using the Gaussian scale-space technique [8]. Niemeijer *et. al.* [6] proposed a pixel classification method where the *KNN* classifier is used with 31 features to classify the pixels in retinal images to vessel and non-vessel pixels, these features are the green channel image, and the filtered image using the Gaussian and its derivatives at different scale values.

In this paper, we propose to use three features only as inputs to the supervised classifier *KNN* to classify the pixels in colour retinal images to vessel and non-vessel pixels. Therefore, the dimensionality of the feature space and the processing time can be reduced. For purposes of comparison, we compare between using the largest eigenvalue, gradient magnitude and the green channel image intensity as features, and the 31 features proposed in [6] to demonstrate the effect of the reduced feature vector on the performance of the classifier and the processing time.

2. FEATURE EXTRACTION AND CLASSIFICATION

2.1. Feature Extraction

The two characterising attributes of any vessel, i.e. piecewise linearity and parallel edges [9], are considered when choosing the set of features for every pixel in retinal images. The piecewise linear property of a blood vessel can be recognised by extracting centerlines of blood vessels, simply by extracting the image ridges. The parallel edges property is well recognised by calculating the gradient magnitude of the image intensity. Because the vessels are of different diameters, so these features are extracted at different scales and then the local maxima over all scales is calculated for both features. In addition to the property that the blood vessel can be seen in the colour retinal image as a dark object on a brighter background, from the three colour channels (red, green and blue) the green channel is chosen to represent this characteristic as it has the highest contrast between the blood vessel and the retinal background.

The features used in this paper are the green channel intensity, the local maxima of the gradient magnitude, and the local maxima of the largest eigenvalue. Fig. 1 shows a sub-image with the intensity information for a blood vessel section is plotted along with the gradient magnitude, the ridge strength and the largest eigenvalue. From

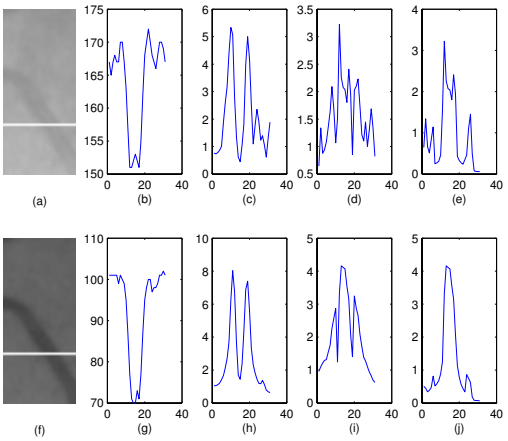


Fig. 1. Sub-image with colour and scale-space features. (a, b, c, d, e) sub-image and its intensity along a horizontal line crossing a blood vessel, gradient magnitude, ridge strength, and largest eigenvalue from red channel image, (f, g, h, i, j) the same but for sub-image from the green channel image.

the graphs, it is clear that the green channel has a higher contrast than the red channel image, gradient magnitude gives two peaks at the parallel edges of the blood vessels, and finally the largest eigenvalue is better than the ridge strength in determining the centerlines of the blood vessels when processing colour fundus images.

The Gradient Magnitude (maximum over scales)

The gradient magnitude is calculated as:

$$|\bigtriangledown L| = \sqrt{L_x^2 + L_y^2} \quad (1)$$

$$L_x = I(x, y) \otimes sG_x$$

$$L_y = I(x, y) \otimes sG_y \quad (2)$$

where L_x and L_y are the first derivative of the image in the x and y directions, G_x and G_y are the Gaussian derivatives in the x and y directions, and s is the scale parameter [8].

The gradient magnitude of the image intensity is calculated at different scales [7], then the local maxima of the gradient magnitude γ is calculated as:

$$\gamma = \max_s \left[\frac{|\bigtriangledown L(s)|}{s} \right] \quad (3)$$

The Largest Eigenvalue (maximum over scales)

The eigenvalues (the large eigenvalue, λ_+, and the small eigenvalue, λ_-) of the Hessian, the matrix of the second order derivatives, of the intensity image $I(x, y)$ are calculated as [7]:

$$\lambda_+ = \frac{L_{xx} + L_{yy} + \alpha}{2} \quad (4)$$

$$\lambda_- = \frac{L_{xx} + L_{yy} - \alpha}{2} \quad (5)$$

where $\alpha = \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2}$

Then, the local maxima of the largest eigenvalue λ_{max} is calculated as :

$$\lambda_{max} = \max_s \left[\frac{\lambda_+(s)}{s} \right] \quad (6)$$

2.2. *K*-Nearest Neighbour Classifier

The nearest neighbour classifier is one of the simplest and oldest methods for performing general, non-parametric classification [10]. To classify an unknown pixel x_q, choose the class of the nearest example in the training set as measured by a distance metric. A common extension is to choose the most common class in the K nearest neighbours. Let an arbitrary pixel x be described by the feature vector:

$$< a_1(x), a_2(x), ...a_n(x) >$$

where $a_r(x)$ is used to denote the values of the rth attribute of pixel x. If we consider two pixels x_i and x_j, then the distance between these pixels is defined as $d(x_i, , x_j)$, which is expressed in Eq. 7

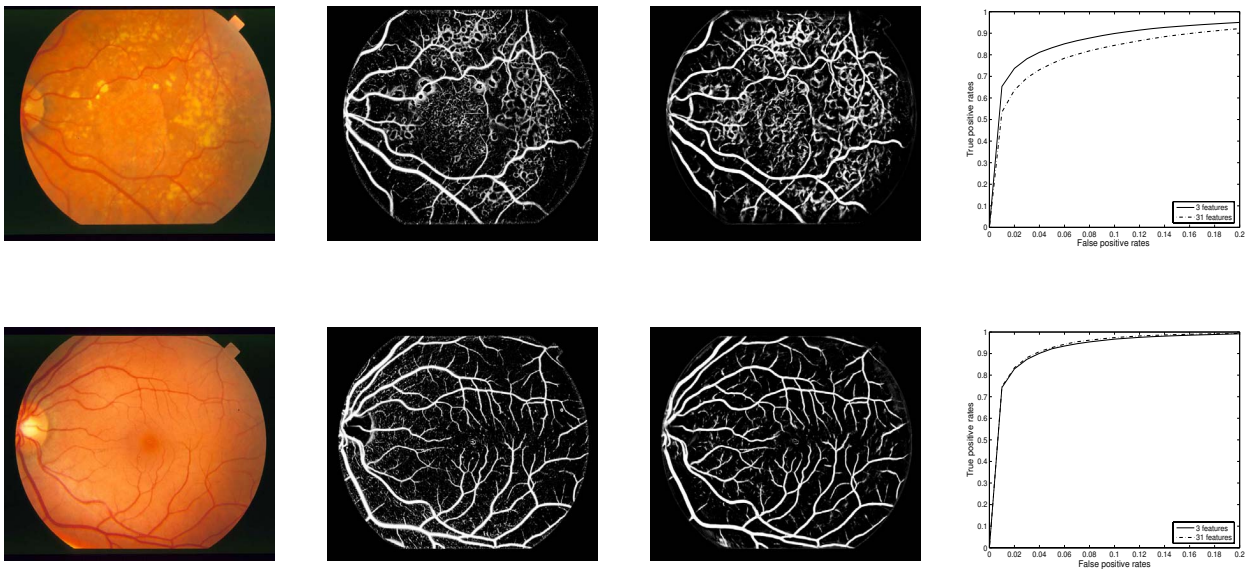
$$d(x_i, x_j) = \sqrt{\sum_{r=1}^{n} (a_r(x_i) - a_r(x_j))^2} \quad (7)$$

For hard classification, the *KNN* output is the most common value among K training examples nearest to x_q, while the mean value of the K nearest neighbour examples is calculated, instead of the most common value, for soft classification.

3. EXPERIMENTS

In our experiments, a set of 20 images publicly available [11] are used, where 10 are normal and 10 contain pathology. For supervised classifiers, two sets are required; one for training and the other for testing. The dataset is randomly divided into two sets of images, each contains 5 normal and 5 abnormal images. The training set contains large number of training samples, which is the main problem with this type of classifiers. To overcome such a problem, a random number of pixels is chosen from the field of view (FOV) of each image in the training set. The targets for these training samples are available from the manually segmented images. The testing set contains 10 images to test the performance of the classifier. For every pixel in each retinal image in the dataset, a feature vector is generated which contains three values - the pixel intensity from the green channel image, the local maxima of the gradient magnitude, and the local maxima of the largest eigenvalue.

Having experimented with different values of K, the value of $K = 60$ appears to offer the best results; hence this value is chosen in our experiments. Furthermore, different normalisation methods have been explored and finally the choice of normalising each feature to zero mean and unit standard deviation offers good performance. The performance is measured with Receiver Operating Characteristic (ROC) curves. An ROC curve plots the false positive rates against the true positive rates, and these rates are defined in the same way as in [12].



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

Fig. 2. (a) Colour images, (b) output of the *KNN* classifier using 3 features, (c) output of the *KNN* classifier using 31 features and (d) ROC curves for images in (b and c).

4. RESULTS AND DISCUSSION

4.1. Results

Figure 2 shows two examples, abnormal and normal images, after blood vessels segmentation using *KNN* classifier with the proposed set of features and the 31 features in [6] and their corresponding ROC curves, In normal image, the two sets of features gives approximately the same results, but in case of abnormal image, the three features give higher sensitivity at the same specificity values. Average ROC curves are considered for specificity and sensitivity analysis and the results for segmentation of retinal blood vessels is summarised in Table 1, where the average sensitivity is calculated at certain specificity values for normal and abnormal images in the testing set. The processing time is significantly decreased when using three features instead of 31 features.

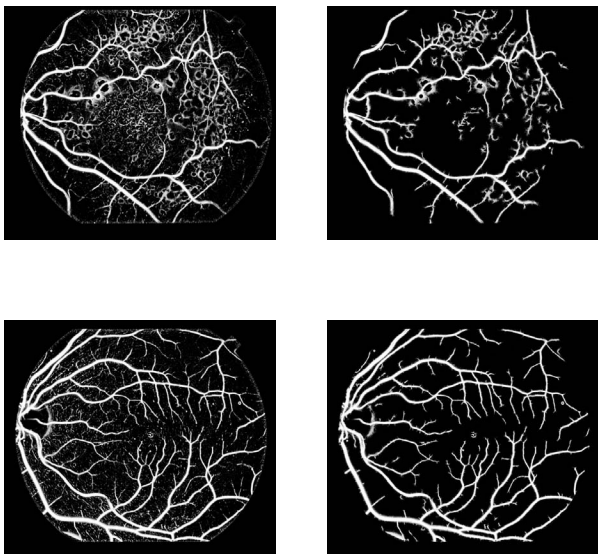
Results obtained from the *KNN* classifier show that there is a need for a post-processing step to remove some connected components that are not blood vessels in order to improve the performance of the classifier. In this step, iterative thresholding strategy to remove small segments is proposed. The processed image (output image from the classifier) is thresholded and segments of size less than 15 pixels are removed, then the threshold value is incremented and small segments are removed and this process is repeated until no more pixels are removed. Fig. 3 shows the effect of removing the small segments on the images in Fig. 2. Further investigations are under way to improve the post-processing step.

Image type	Specificity %	3 Features Sensitivity %	31 Feature Sensitivity %
Normal		86.60%	89.24%
Abnormal	95%	76.24%	77.91%
Normal		92.56%	94.32%
Abnormal	90%	86.13%	86.19%
Normal		95.03%	96.40%
Abnormal	85%	90.89%	90.18%
Normal		96.51%	97.45%
Abnormal	80%	93.65%	92.67%
Processing time		33%	100%

Table 1. Average sensitivity at certain specificity values and processing time for 3 and 31 features.

4.2. Discussion

As demonstrated in Table 1, at specificity of 90%, the proposed three features gives promising results of 93% and 86% sensitivity for normal and abnormal images respectively compared with the pixel classification method that uses a set of 31 features and gives 94% and 86% sensitivity for normal and abnormal images. Furthermore, at specificity of 95%, the sensitivity of the proposed method is 87% and 76% compared with 89% and 78% sensitivity of the pixel classification method for normal and abnormal images respectively. One of the factors that should be considered when using supervised classifiers is the size of feature vector. As the size of the feature vector



(a) (b)

Fig. 3. Effect of post-processing (a) before, and (b) after post-processing.

increased, the processing time is increased, as shown in Fig. 4.

5. CONCLUSIONS

In this paper, we have proposed to use feature vectors of three features each with the *KNN* classifier to classify the pixels of retinal images as vessel pixels or non-vessel pixels. The local maxima of the largest eigenvalue has been proposed to be used as a feature in addition to the green channel and the local maxima of the gradient magnitude of the intensity image. Results have shown that using these three features significantly reduces the processing time with comparable sensitivity to the pixel classification method that uses 31 features.

6. ACKNOWLEDGMENT

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7. REFERENCES

[1] C. Sinthanayothin, J.F. Boyee, T.H. Williamson, H.L. Cook, E. Mensah, S. Lal, and D. Usher , "Automatic Detection of Diabetic Retinopathy on Digital Fundus Images," *Diabetic Med.*, vol. 19, no. 2, pp. 105-112, Feb. 2002.

[2] F. Zana and J. Klein, "A Multimodal Registration Algorithm of Eye Fundus Images using Vessels Detection and Hough Transform," *IEEE Trans. Med. Imag.*, vol. 18, no. 5, pp. 419-428, May 1999.

[3] A. Pinz, S. Bernögger, P. Datlinger, and A. Kruger, "Mapping the Human Retina," *IEEE Trans. Med. Imag.*, vol. 17, no. 4, pp. 606-619, Aug. 1998.

[4] A. Hoover and M. Goldbaum, "Locating the Optic Nerve in a Retinal Image using Fuzzy Convergence of the Blood Vessels," *IEEE Trans. Med. Imag.*, vol. 22, no. 8, pp. 951-958, Aug. 2003.

[5] J. Staal, M.D. Abramoff, M. Niemeijer, M.A. Viergever, and B. van Ginneken, "Ridge-Based Vessel Segmentation in Color Images for the Retina," *IEEE Trans. Med. Imag.*, vol. 23, no. 4, pp. 501-509, April 2004.

[6] M. Niemeijer, J. Staal, B. van Ginneken, M. Long, and M.D. Abramoff, "Comparative Study of Retinal Vessel Segmentation Methods on a New Publicly Available Database," *Proc. SPIE Med. Imaging*, vol. 5370, pp. 648-656, 2004.

[7] M.E. Martínez-Pérez, A.D. Hughes, A.V. Stanton, S.A. Thom, A.A. Bharath, and K.H. Parker, "Scale-Space Analysis for the Characterisation of Retinal Blood Vessels," In *Medical Image Computing and Computer-Assisted Intervention - MICCAI'99*, C. Taylor and A. Colchester, Eds., pp. 90-97, 1999.

[8] T. Lindeberg, *Scale-Space Theory in Computer Vision*, Kluwer Academic Publisher, Netherlands, 1994.

[9] J. Kansky, *Clinical Opthalmology*: *a systematic approach*, Butterworth-Heinmann, Oxford, 4th ed., 1999.

[10] R. Duda, P. Hart, and D. Stork, *Pattern Classification*, John Wiley and Sons, New York, 2nd ed., 2001.

[11] The STARE project, available at `http://www.ces.clemson.edu/~ahoover/stare`

[12] A. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating Blood Vessels in Retinal Images by Piecewise Threshold Probing of a Matched Filter Response," *IEEE Trans. Med. Imag.*, vol. 19, no. 3, pp. 203-210, Mar. 2000.

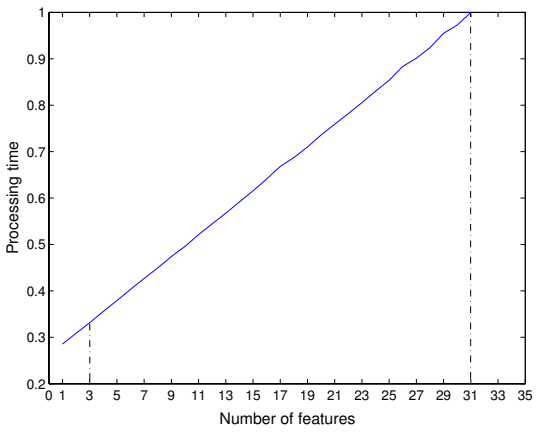

Fig. 4. Effect of number of features on processing time.