Blood Vessel Segmentation from Color Retinal Images Using K-Means Clustering and 2D Gabor Wavelet

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Abstract This paper presents a new unsupervised method for segmenting blood vessels in digital retinal images. The proposed method uses K-means clustering to binarize grayscale vessel-enhanced images derived from green channel image and Gabor wavelet feature image. The binary images are then combined using logical OR to produce segmented vessels. The method was evaluated on the publicly available DRIVE database and the results compared to published literature. The method proved to have comparable performance to other published unsupervised methods while being simple and fast to implement. In the future, the proposed method can be further improved to be applied in real clinical setting to assist the physicians in diagnosing ocular diseases through an automated screening system.

Keywords Retinal image · Blood vessel segmentation · K-means clustering · Gabor wavelet

1 Introduction

Accurate detection and measurement of retinal blood vessels from digital retinal image is very important for early screening of disease onset and also in quantifying the severity of ocular diseases. A reliable method of segmenting the retinal blood vessels is necessary towards the development of automated diagnosis system for retinal images. While manual segmentation is possible, the amount of effort and time needed for even a small set of images could eventually become prohibitive.

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This is one of the reasons a large number of researchers have been investigating the topic of automatic segmentation of retinal blood vessels in the recent years.

An extensive summary of previous works on blood vessel segmentation methodologies was presented in [1], where the methods of segmenting retinal blood vessels were divided into five main approaches namely pattern classification, matched filtering, morphological processing, vessel tracking and multi-scale approaches.

Pattern recognition approach with supervised classification method have been employed in [2–4], and in [5] Soares et al. proposed the use of Gaussian Mixture Models classifier to classify Gabor wavelet features extracted from retinal images. Matched filtering method was initially proposed by Chauduri in [6] which inspired more extended work by Hoover [7] and Zhang [8]. Zana and Klein [9] adopted morphological processing method to segment retinal blood vessels while Mendonca et al. [10] combined it with centerline detection. In [11], Strisciuglio employed a set of trainable B-COSFIRE filters to better capture the elongated structure of retinal blood vessels.

This paper proposes an unsupervised method to perform automated segmentation of blood vessels on retinal images that is inspired by the use of Gabor wavelet filter in a number of previous studies, for example in [5, 12]. As opposed to the use of supervised classification methods to binarize the Gabor feature in previous studies, we propose the use of K-means clustering to binarize the Gabor wavelet feature, which is simpler to implement and more efficient for processing a huge number of retinal images.

2   Proposed Method

The proposed method of automatic retinal vessel segmentation is divided into four main parts. In Part 1, pre-processing is performed on the green channel image obtained from the original color retinal and then enhanced to highlight blood vessels. In Part 2, the green channel image is inverted and Gabor wavelet feature is extracted. The Gabor feature then undergoes vessel-enhancement process. In Part 3 of the proposed method, K-means clustering are performed on the two vessel-enhanced images from the previous part separately, resulting in binary images that later go through post-processing. The final segmentation output is then produced in Part 4 by combining the two binary images using logical OR operation after which a final post-processing step is performed.

Pre-processing. Since green channel of the color retinal image provides highest contrast between retinal background and blood vessels, it will be used as the initial input in the proposed method. The Field-of-View (FOV) region in the green channel image is expanded according to Soares's recommendation in order to minimize effects from the high contrast between FOV and black background [5].
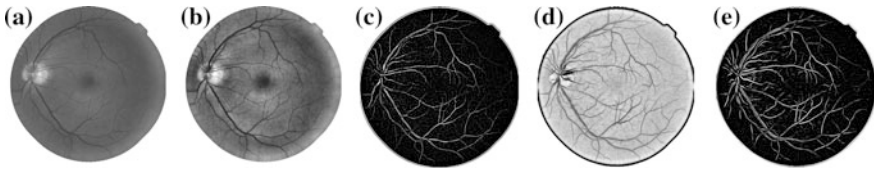
Fig. 1 Sample green channel image and its corresponding pre-processing output: **a** Green channel image with padded FOV, **b** contrast-adjusted green channel image, **c** vessel-enhanced green channel image, **d** contrast-adjusted Gabor feature image, and **e** vessel-enhanced Gabor feature image

Blood vessels on the padded green channel image are then first enhanced using contrast-limited adaptive histogram equalization (CLAHE) method. After the contrast is adjusted, the mean image is obtained by convolving the contrast-adjusted image with a mean arithmetic kernel. The mean image is later subtracted from the contrast-adjusted image and the resulting image is contrast-adjusted again to further enhance the vessels resulting in a vessel-enhanced image.

Gabor Wavelet. We used the same parameters as proposed by Soares in [5] in our method to derive Gabor wavelet response of inverted green channel image obtained from the previous step. The Gabor wavelet response is further processed to produce a vessel-enhanced Gabor wavelet feature image. Figure 1 shows a sample of green channel image with its corresponding contrast-adjusted and vessel-enhanced images for both green channel and Gabor feature.

Binary Thresholding. After obtaining both vessel-enhanced images from green channel and Gabor wavelet feature, K-means clustering is performed on both grayscale images to produce binary vessel images. The number of cluster for K-means clustering is set to two clusters, one for a vessel pixel (value 1) and another for background pixel (value 0). The output of this step normally contains noisy pixels which are mostly background pixels detected as disconnected vessel pixels. The objective of the next step is to remove as much of these noisy pixels as possible, without removing actual vessel pixels.

Image Post-processing. In this step, noisy pixels and small regions that mostly do not represent blood vessels are removed. This is achieved by adopting a morphological operation called opening to remove any connected vessel pixels containing less than a threshold value, which has been empirically determined to be 50 pixels for green channel binary image and 25 pixels for Gabor feature binary image.

Binary Image Combination. After the images have been individually post-processed, they are then combined using the logical OR operation to produce a single binary image. A final post-processing step using morphological opening is performed on the combination output. The result is a binary image representing the vessels from both green channel and Gabor feature binary images, as illustrated in Fig. 2.
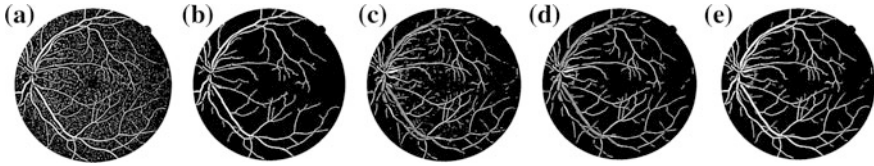
Fig. 2 Clustering, post-processing and binary image combination outputs: **a** Binary image from green channel, **b** post-processed green channel image, **c** binary image from Gabor feature, **d** post-processed Gabor feature image, and **e** result of OR operation on images 2(**b**) and 2(**d**)

3 Results and Discussion

3.1 Image Database

Our proposed method was evaluated using retinal images from the publicly available DRIVE database [7]. The database contains 40 color retinal images which are divided into two sets, namely training set and test set. The image size is 565 by 584 pixels with 8 bits per color channel and they were captured using a Canon CR5 non-mydriatic camera with a field of view of 45°. For each image in the database, the authors also provide its corresponding mask image and a manual segmentation image. For the test set, a second set of manually segmented images are also included. In our evaluation, we used the test set for testing with the first set of manual segmentation (1st human observer) as ground truth. We use the second manual segmentation (2nd human observer) set as the target benchmark for our method.

3.2 Performance Metric

A number of different performance measure have been described in the literature to evaluate vessel segmentation algorithm. For performance measure assessment in this study, only pixels within the FOV are considered. A true positive (TP) is defined as a pixel identified as vessel by the algorithm and is also specified as vessel in ground truth image. A false positive (FP) is a vessel identified as vessel by the algorithm but specified as non-vessel in ground truth image. Any vessel identified as non-vessels by the algorithm but marked as vessel in ground truth is a false negative (FN) and true negatives (TN) are pixels identified as non-vessels by both algorithm and ground truth image. The counted values for all TP, FP, TN and FN can be used to calculate the performance measure of a vessel segmentation algorithm. We have selected a number of usual measures used in previous literature which includes Accuracy rate (ACC), Sensitivity (SN), Specificity (SP) and Matthews Correlation Coefficient (MCC) in order to quantify the performance of our

proposed method. We used the same formulas specified in [11] to calculate the performance metric for our results.

3.3 Experimental Results

Before the binary images were combined, performance measures were calculated for binary images from green channel and binary images from Gabor feature image individually. 2nd human observer's performance was obtained by comparing the 2nd observer's segmentation to the 1st observer's segmentation outputs which were used as the ground truth in this study. From the results in Table 1, segmentation outputs using only green channel image performs better than the outputs using only Gabor feature image on all metrics considered except sensitivity. However sample binary images from both feature in Fig. 2 indicates that Gabor feature (Fig. 2d) is better in capturing finer vessels compared to green channel image. This could be due to the chosen value of 2 pixels for Gaussian envelope scale parameter, σ that highlights fine vessels well. While this is true, some of the larger vessels appear hollow due to the central vessel reflex on Gabor binary image. This can be complemented by the binary image from green channel that preserves most of the large vessels well, contributing to a much improved results when the two binary images combined as shown in the last row of Table 1.

Results for Zana, Chaudhuri and Jiang are calculated using the output images provided on DRIVE database website, while other results are obtained from the published literature. The proposed method has an average accuracy of 0.9425

Table 1 Performance of proposed method compared to other published methods

Methods	SN	SP	ACC	MCC
2nd human observer	0.7763	0.9723	0.9470	0.7660
Green channel image	0.5987	0.9884	0.9378	0.7021
Gabor feature image	0.6062	0.9787	0.9306	0.6716
Zana[a] [9]	0.6697	0.9830	0.9429	0.7315
Chaudhuri[a] [6]	0.2706	0.9887	0.8969	0.4236
Jiang[a] [13]	0.6480	0.9623	0.9218	0.6509
Strisciuglio [11]	0.7655	0.9704	0.9442	0.7475
Mendonca [10]	0.7344	0.9764	0.9452	–
Proposed method	**0.7206**	**0.9757**	**0.9425**	**0.7400**

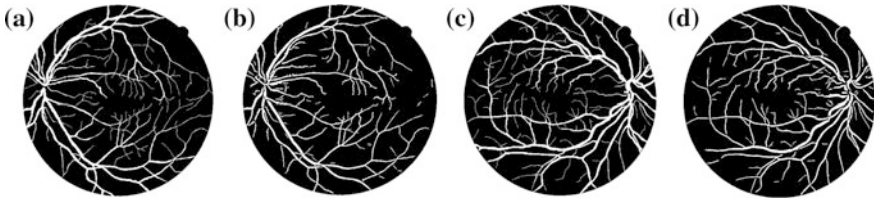[a]Results calculated from provided binary images on DRIVE website

Fig. 3 Sample vessel segmentation outputs of Image 12 and 2 from DRIVE database. **a** Ground truth Image 12 from DRIVE database, **b** final segmented vessels of Image 12, **c** Ground truth Image 2 from DRIVE database, and **d** final segmented vessels of Image 2

which are comparable to other methods' results with highest accuracy of 0.9452 by Mendonca. The proposed method's sensitivity value of 0.7206 is higher than Zana, Chauduri, and Jiang but slightly lower than Strisciuglio and Mendonca. In terms of specificity, the proposed method has the value of 0.9757 which is comparable to other published methods. Strisciuglio's method recorded highest MCC value of 0.7475 while the proposed method has the second highest MCC value of 0.7400. Specificity value of our method also exceeds those of second observer's manual segmentation results. Figure 3 compares 2 sample outputs with their corresponding manual segmentation outputs, i.e. the ground truth.

4 Conclusion

We proposed a novel retinal blood vessel segmentation method that combines binary images obtained from the vessel-enhanced green channel image and vessel-enhanced Gabor feature image. The binary images are produced using unsupervised K-means clustering and combined using logical OR operation. The combination of binary images increased the performance of individual features by complementing each other well. The results achieved (SN = 0.7206, SP = 0.9757, ACC = 0.9425 and MCC = 0.7400) are comparable to published unsupervised methods. The proposed method is efficient since it does not involve sophisticated calculations nor prior training of labeled images. In future work, other methods of image combination will be investigated to improve the overall performance of the segmentation method.

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