



Self-organizing Map for Blood Vessel Segmentation of Fundus Images

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Abstract. Blood vessel segmentation is a topic of high interest in fundus image analysis. This paper presents a clustering method to segment the blood vessels automatically from the fundus images. Our proposed method integrates with the wavelet transform, the morphological transformation and self-organizing map (SOM). Firstly, we extract a multi-dimensional feature vector of every pixel in the fundus image by wavelet transform and morphological operation. Then, the SOM network is integrated with K-mean method to cluster pixels. Finally, we validate the accuracy of our proposed method on DRIVE database, and compare our proposed method with other methods.

Keywords: Wavelet transform · Fundus images · Self-organizing map

1 Introduction

Detecting, diagnosis and controlling eyes diseases require the precise and real information of the fundus blood vessels structure [1]. Manual detection of the fundus blood vessels is time consuming and difficult, because the fundus image shows low contrast and noise [2]. Automatic segmentation of blood vessels from fundus images can reduce the work of doctors and provide more useful information for the retinal disease diagnosis.

Many methods have been proposed for fundus vessel segmentation, including rule-based method and machine learning methods. The rule-based methods include model-based methods [3–5], kernel-based methods [6, 7], and adaptive thresholding methods [8, 9]. The machine learning method is divided into supervised and unsupervised method. The supervised methods train the classifier with the prior knowledge, including support vector machine, Bayesian classifier and K-nearest neighbor classifier [4, 10, 11]. The unsupervised methods segment blood vessels without any prior knowledge, including fuzzy C-mean method, K-mean algorithm and self-organizing map [12, 13].

This paper presents an unsupervised method to segment blood vessels from the fundus images automatically without any prior knowledge. Firstly, we extract a three-dimensional feature vector with wavelet transform and morphological operation in order to improve the accuracy of segmentation. Then, we exploit SOM as our classifier, and cluster the output neurons of SOM with K-mean algorithm.

The rest of our paper is organized as follows. In Sect. 2, we propose our automatic unsupervised method for fundus image segmentation. In Sect. 3, we presents the experimental results, and we give the conclusions in Sect. 4.

2 Our Proposed Unsupervised Segmentation Method

2.1 Multi-dimensional Feature Extraction

Because there are some problems in fundus image acquisition, such as poor contrast and high variability [14], the segmentation results based on simple pixel intensities are not accurate. Therefore, a three-dimensional feature vector of each pixel is constructed from the fundus image to improve the accuracy of segmentation.

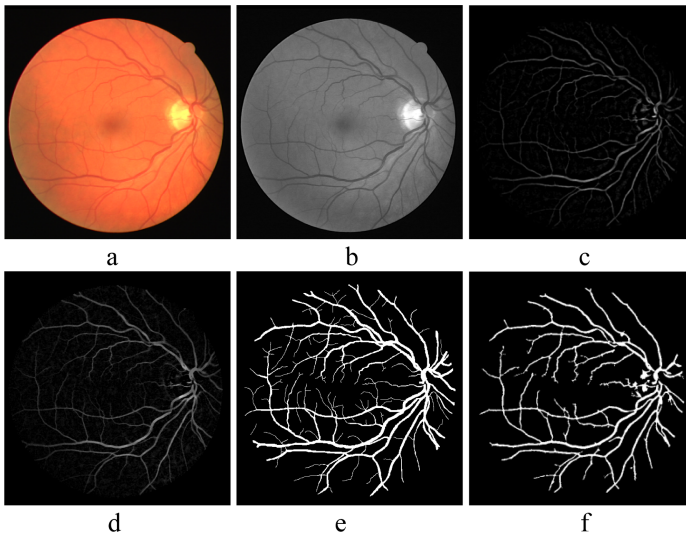


Fig. 1. The feature extraction from a fundus image. (a) The RGB fundus image. (b) The image in the green channel. (c) The high-frequency db4 wavelet image with scale two, three and four. (d) The enhancement image with morphological transformation. (e) The ground truth segmented by the first specialist. (f) Our segmentation result with the unsupervised method.

The image in the green channel of RGB fundus image has better vascular-background contrast than the images in the red channel and blue channel [10, 14]. Therefore, the intensity of green channel is taken as the intensity feature of each pixel. Figure 1(a) is a RGB fundus image from DRIVE database, and Fig. 1(b) is the image in the green channel of Fig. 1(a).

Fundus images often show noise and poor contrast [14]. Wavelet method can decompose the fundus image into different orientations and scales. We extract the wavelet feature from the high-frequency subbands of db4 wavelet transform with scale two, three and four. The high-frequency wavelet image with scale two, three and four of Fig. 1(b) is shown in Fig. 1(c).

For removing the background lightening variations in the fundus image, we exploit the shade-correction method [13] in our paper. But the shade-correction processing deteriorates the contrast between background and blood vessels. Therefore, we apply the morphological top-hat transformation on the complementary image after the shade-correction processing. Figure 1(d) is the enhancement image with morphological top-hat transformation.

Therefore, we extract a three-dimensional feature vector for the fundus image pixels with the image in the green channel, the high-frequency features of the wavelet transform and vessel enhancement feature by morphological transformation.

2.2 Segmentation Method Based on Unsupervised Neutral Network

Self-organizing map proposed by Kohonen [15] is a two-layer feedforward competitive learning neural network. During training process, it can cluster the training data to the same neuron or neighboring neuron in one or two dimensional space without any prior knowledge. Therefore, SOM is widely used as an unsupervised neural network in automatic medical image segmentation [10]. In this paper, we use SOM network for pixel clustering.

In our experiment, SOM has one input layer and one output layer. The SOM with only two neurons in the output layer can't accurately segment the small and thin blood vessels from the fundus image. So, the output layer is a 4×4 array consisted by 16 neurons in our experiments, where every output neuron i has a weight vector w_i .

In the training step t , we randomly select the input pixel p from the fundus image I , and calculate the distance $d_{v_p,i}(t)$ between the weight of output neuron i and the input feature vector v_p . The neuron c whose weight vector is closest to the input feature vector v_p is selected as the winning neuron.

Then, we update the neurons' weight in the neighborhood of neuron c with the equation $w_i(t+1) = w_i(t) + \alpha(t)N_r(c,i)(v_p(t) - w_i) \forall i \in N_c, p \in I$, where

- N_c is the set of neighboring neurons of neuron c , and its neighborhood radius decreases with time t .
- $N_r(c,i)$ is the activation function in the neighborhood of winning neuron c at time t , representing the activation degree of neuron i . In our experiment, we exploit Gaussian function as the neighborhood activation function

$$N_r(c,i) = \exp\left(-\frac{\|r_i - r_c\|^2}{2N_c^2(t)}\right)$$

where r_i is the coordinate of neuron i in the output layer, and $N_c(t)$ is the neighborhood radius of winning neuron c at time t .

- The parameter $\alpha(t)$ is the learning rate, and it monotonically decreases with time [15, 16].

After the training process of SOM, K-mean method is exploited to determine the class of output neurons, which labels the neurons' class according to the distance from each other. At last, we input the pixel feature vector of the testing fundus image into the trained SOM and get the final segmentation result. Our segmentation result of Fig. 1(a) is shown in Fig. 1(f), and the ground truth shown in Fig. 1(e).

3 Experimental Results

The DRIVE database [17] is a public database with the color fundus images with size 565×584 . Researchers often use it to verify their segmentation methods. In addition, the DRIVE database has also provided two sets of results manually partitioned by two specialists as the ground truth. In our experiments, the DRIVE database is used and the segmentation results by the first specialist are exploited as the ground truth. Accuracy index is exploited in our experiments to quantify the overlap between the ground truth and our segmentation results.

Table 1. Comparing the segmentation results of our proposed method with the other methods on the DRIVE database in terms of the average accuracy value.

Method type	Method	DRIVE
Rule-based method	Martinez Perez et al. [18]	0.934
Model-based method	Jiang X. et al. [8]	0.891
Matched filter	Chaudhuri S. et al. [19]	0.877
	Cinsdikici M. G. et al. [20]	0.929
Supervised method	Niemeijer M. et al. [21]	0.941
Unsupervised method	Our proposed method	0.935

For comparing our proposed method with other segmentation methods, we use the average accuracy value as a measure of method performance. In our experiments, the average accuracy value of our proposed unsupervised method is 0.935. The DRIVE database has provided the segmentation results with the methods proposed by Jiang X. et al. [8], Martinez Perez et al. [18], Cinsdikici M. G. et al. [20], Chaudhuri S. et al. [19] and Niemeijer M. et al. [21]. We compare the segmentation results of our proposed method with other methods mentioned above, and list the comparison results in Table 1. Table 1 shows that our proposed method is superior to most other methods.

4 Conclusions

Our study proposes a blood vessel segmentation method based on the unsupervised neural network. Firstly, we extract the input feature vector with the wavelet transform and the morphological operation, which improves the segmentation results. Then, we cluster the pixels in the fundus image with SOM method, and classify the output neurons as vessel class or non-vessel class with K-mean method. All the processing mentioned above is automatic, and does not need any prior knowledge.

We validate the accuracy of our proposed method on DRIVE database. The experimental results indicate that our proposed method achieves good results in fundus image segmentation. Moreover, we also compare the segmentation results of our proposed method with other segmentation methods, and the experimental results show that our proposed method is superior to most other methods.

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