Locating blood vessels in retinal images using unified Textons

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Abstract

Our research aims to investigate retinal image segmentation approaches based on textons as they provide a compact description of texture that can be learnt from a training set. We propose a new filter bank which is designed for feature extraction. The K-means clustering algorithm is adopted for texton generation. We back project textons onto the ground truth in a machine learning stage to identify the corresponding vessel textons and these are subsequently used to identify vessels in the test set. To verify that these unified textons provide a general tool that can be used for vessel segmentation, we perform experiments on three different data sets, generating textons from the one set, and testing on another two data sets. Our results show the method outperforms other published work, and reveal that it is possible to train unified textons for retinal vessel segmentation.

1 Introduction

Vessel segmentation plays an important role in early automatic detection of diabetic retinopathy, it also contributes to other clinical purposes in computer aided diagnostics and treatments such as glaucoma [1], hypertension, obesity, arteriosclerosis and retinal artery occlusion by measuring vessel diameter [2][3], and computer-assisted laser surgery [4]. The previous methods or algorithms that have been presented for retinal vessel segmentation fall into three categories: filtering-based methods, trace-based methods and classifier-based methods. In filter-based research, the classic matched filter (MF) introduced by Chaudhuri et al. [5] is a popular approach. Because of its advantages of simplicity and effectiveness, the MF has been applied by other researchers for a long time. However, the classic MF has a limitation that it's hard to detect small branches of blood vessels. Given its advantages and limitations, MF attracted extensive research in applications of blood vessel detection. For instance: Gang et al. [6] studied the Gaussian function model used by Chaudhuri et al. [5] further and an amplitude-modified second-order Gaussian filter is proposed. They optimized the parameters of the matched filter via mathematical analysis and experimental simulation. Bob and Lin et al. [7] proposed a novel extension of the MF approach which is named MF-FDOG to distinguish vessel from non-vessel step edges. It enhances the function of the MF that discriminates vessel structure from non-vessel structure and detects the small branches of vessels which are miss-detected by a basic MF. Tracking methods proceed by first determining start points within the incomplete global skeleton of blood vessels and then track the vessels from those points according to some local image features. Echevarria and Miller [8] propose a method that utilizes the level sets concept to remove the noise and use the fast marching method [19] to trace vessels. The critical factor of classifier-based retinal segmentation methods is the selection of a classifier. Diego Marín et al. [9] adopt a neural network (NN) to achieve pixel classification task and in [10] a Bayesian classifier with class-conditional probability density functions derived from a Gaussian mixture model (GMM) was adopted to identify whether pixels are vessel or not.

Although automatic segmentation of the blood vessel networks has been studied widely, it is still a big challenge and retinal vessel segmentation remains a focus for ongoing research. In our experiments, we focus on texture-based segmentation techniques known as textons as only a few authors [18] have investigated this approach for retinal vessel segmentation and it provides an approach for learning texture features which is founded in human perception.

Texton-based approaches have been a significant branch of texture analysis process since the term texton was introduced by Julesz in the 1980's [11]. The name 'Texton' was defined as an element which can represent a particular density of local image features. Leung and Malik [12] described an operational definition of textons using a framework that enables most textures to be decomposed into a small number of vectors, which can be modelled by calculating cluster centres from a filter response space. The motivation of our experiment comes from Varma and Zisserman's [13] work which achieved success in classifying a range of natural texture patterns. In our experiment, we proposed a novel texton based retinal segmentation method. Moreover, to pursue an automatic vessel segmentation method that doesn't require extensive retraining and is robust to noise and variation in image capture, we performed experiments on retinal images captured at three different hospitals. Our analysis verified that textons trained on one data set can be reused on other data sets. The rest of the paper is organized as follows. Our proposed method is described and explained in section 2. Section 3 presents our experimental results and conclusions and further work are discussed in the final section.

2 Method

2.1 Materials

Our initial experiments were carried out using the STARE [14] and DRIVE [15] datasets and subsequently evaluated on an additional data set from Manchester Eye Hospital. The images of the STARE dataset were stored as PPM format and digitized to a size of 700×605. The dataset contains manual segmented ground truth results made by two observers. The first set of manual segmentation results is used as ground truth in our experiment. The DRIVE dataset contains 40 TIFF formatted RGB retinal images with a size of 565×584 pixels. Each dataset comprises images of which have been hand labelled by two pathologists. In our experiment, we chose the first observer's performance as ground truth. To evaluate the approach we test on another data set comprising 20 images collected from Manchester Eye Hopital. These are also hand labelled by a pathologist.

In our experiment, the performance is evaluated in terms of sensitivity, specificity, and accuracy.

2.2 Filer bank MR11

We designed a new filter bank for the dissection of bar structures (vessels). The vessels are modelled as local line or bar structure objects, and we focus on extracting this single object (vessels) from the background instead of classifying multiple objects. So it's not necessary to adopt the first-order derivative Gaussian filter but instead second-order derivative Gaussian filters with three scales (scale (σ x, σ y) ={(1,3), (1.5,4.5),(2,6)}) are applied. The first 3 rows in Fig. 1 illustrate these filters. To address the vessels' reflection problem, we use the Difference of Gaussians (DoG) filter response. Equation (1) defines a general Gaussian function. The offset parameter δ in Equation (2) represents the distance between the centers of the Gaussian kernels in a DoG filter

$$\mathbf{I_{\sigma}(x, y)} = \frac{\mathbf{1}}{\sqrt{\mathbf{2\pi\sigma}}}\mathbf{e}^{\left(-\frac{\mathbf{x^2+y^2}}{\mathbf{2\sigma^2}}\right)} \quad (1)$$

$$DOG_{\sigma}(x, y) = I_{\sigma}(x, y) - I_{\sigma}(x + \delta, y) \quad (2)$$

In practice, this offset parameter is the centre position of the vessel over a cross section, the values in our experiments, chosen as 0.5, 0.75 and 1 pixels are based on values of σ.We also add a matched filter as a specific bar detector. For the parameters σ and L we choose σ equals 1, 1.5, 2 pixels respectively and L equals 9 which was deemed as an optimized value in [5]. σ is the standard deviation which defines the spread of the intensity profile, and L is the length of the vessel segment that has the same orientation. The second-order derivative Gaussian filter (2DG), DoG and Matched filer (MF) are anisotropic filters. To detect vessels in different orientations, filter kernels are rotated over 12 orientations. The last 2 isotropic filter categories (109, 100) are Gaussian and LoG filters, we choose the same parameters for these filters as their equivalents in MR8 [13]. The filter bank is visualized in Figure 1.

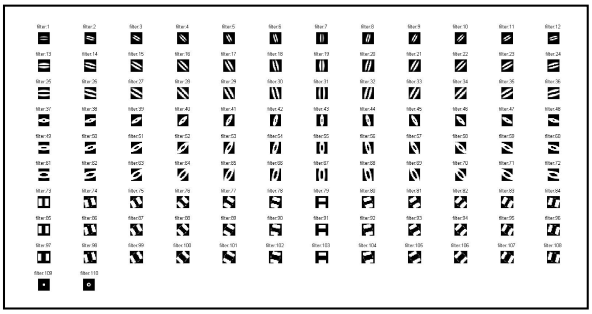

Figure 1. New Filter bank MR11

2.3 Generating the Texton

In our experiment, the Texton computing procedure comprises two primary stages (training and testing): At the training stage, we choose 10 images as a training sample. We apply the MR11 filter bank on this training sample to get the 11 filter responses, these 11 responses are aggregated into a single data cell. The texton is generated by applying a k-means algorithm on the filter responses. The flowchart of this algorithm is illustrated in Fig.2. Given the structures within the retinal image, normally each scan consists of the background, the vessels, the optic disc (OD), and other pathologic units (particularly, existing in the image of patient). In our experiment, the total number of learnt textons is k=5, where k is the cluster centre number.

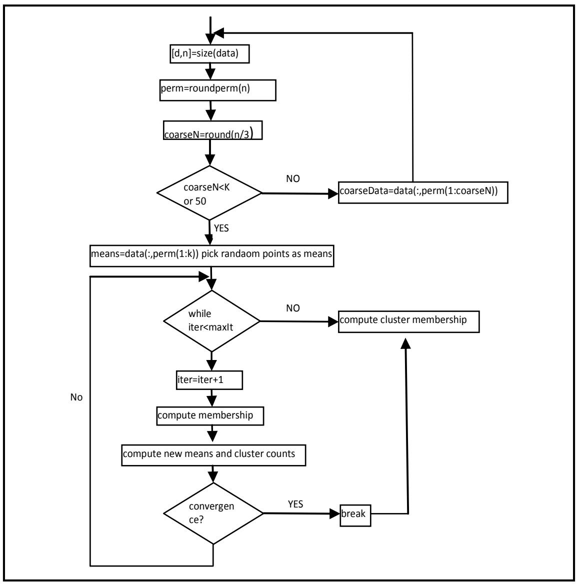

Figure 2. Flowchart of Texton generation algorithm

2.4 Indicating vessel Texton and Segmentation

After the texton generation stage, each texton is given a unique ID, and the corresponding texton maps obtained by using every texton. Although we now have the 5 textons, the system can't recognize which texton membership belongs to vessels and which represent non-vessels (background); for this we use the ground-truth. In order to get vessel texton, all texton ID are then sorted by ID and the texton responses are back-projected into the training set, those which have the maximal number of corresponding membership (pixels) is removed from the list, since this indicates the background. The rest of textons are used in training to identify optimized combinations that are subsequently used for vessel detection. For instance, we got four texton ID which are 1,2,3,4 respectively. There are 11 combinations of these four texton relative memberships (tmap), namely, (1,2), (1,3), (1,4), (2,3), (2,4), (3,4), (1,2,3), (1,2,4), (1,3,4), (2,3,4) and (1,2,3,4). Every combination is evaluated by calculating the accuracy compared to the ground truth. The combination with highest accuracy is defined as the vessel texton. Both these textons and vessels texton ID are stored. These textons are used in the test stage. In testing, firstly, the same filter bank MR11 is applied on a novel image and 11 responses are generated. Next, the texton data are assigned to the responses and the corresponding texton memberships are generated by calculating the minimal Euclidean distance from the vectors of responses assigned to the centres of textons. Hence we label each filter response with the corresponding texton and finally, the segmentation is completed by combining the vessel texton ID memberships.

3 Experiment results

Firstly the proposed method was tested and evaluated on both STARE and DRIVE experimental data sets. In order to quantify the performance of the proposed approach, the resulting segmentation is compared to its corresponding ground truth. The ground truth is obtained by manual creation of a vessel mask in which all vessel pixels are set to one and all non-vessel pixels are set to zero. Our algorithm was evaluated in terms of sensitivity, specificity and accuracy. On the STARE dataset, average specificity reaches 0.9643 with 0.7515 sensitivity, the accuracy is 0.9506. The terms of specificity, sensitivity and accuracy for the DRIVE dataset are 0.9831, 0.7167, and 0.9591 respectively.

Method	**Performance Results**			
	database	***Sensitivity***	***Specificity***	***Accuracy***
Our method	STARE	**0.7515**	**0.9643**	**0.9506**
Hoover[14]	STARE	0.6751	0.9567	0.9275
Soares [10]	STARE	0.7165	0.9748	0.9480
Diego [9]	STARE	0.6944	0.9819	0.9526
Staal [15]	STARE	0.6970	0.9810	0.9516
Zhang [7]	STARE	0.7177	0.9753	0.9484
Our method	DRIVE	**0.7167**	**0.9831**	**0.9591**
Mendonca [17]	DRIVE	0.7344	0.9764	0.9425
Soares [10]	DRIVE	0.7283	0.9788	0.9466
Zana [16]	DRIVE	0.6696	0.9769	0.9377
Staal [15]	DRIVE	0.7194	0.9773	0.9441
Zhang[7]	DRIVE	0.7120	0.9724	0.9382

Table 1: comparative results on stare database and drive database

In order to compare our approach to other retinal vessel segmentation algorithms, the average sensitivity, specificity and accuracy were used as measures of performance. Table 1 shows comparative results confirming that the performance compares well with the best published results on both datasets.

Image	Sensitivity		Specificity		Accuracy	
	D*	N*	D*	N*	D*	N*
01test	0.8539	0.8037	0.9660	0.9327	0.9560	0.9169
02test	0.7938	0.7618	0.9758	0.9815	0.9571	0.9657
03test	0.7212	0.7767	0.9760	0.9569	0.9506	0.9383
04test	0.7806	0.8098	0.9683	0.9488	0.9510	0.9364
05test	0.7223	0.7902	0.9839	0.9556	0.9594	0.9355
06test	0.7055	0.8169	0.9814	0.9473	0.9545	0.9357
07test	0.7578	0.7935	0.9645	0.9463	0.9456	0.9337
08test	0.7082	0.8670	0.9676	0.9647	0.9453	0.9567
09test	0.7232	0.8496	0.9811	0.9527	0.9602	0.9424
10test	0.7529	0.7460	0.9763	0.9509	0.9579	0.9303
11test	0.7631	0.8326	0.9668	0.9580	0.9486	0.9466
12test	0.7896	0.8387	0.9687	0.9505	0.9532	0.9413
13test	0.7594	0.6961	0.9696	0.9572	0.9490	0.9284
14test	0.8230	0.8094	0.9593	0.9542	0.9483	0.9403
15test	0.8323	0.7852	0.9513	0.9638	0.9428	0.9494
16test	0.8063	0.8297	0.9730	0.9423	0.9580	0.9327
17test	0.7786	0.7828	0.9662	0.9433	0.9504	0.9293
18test	0.8273	0.7378	0.9682	0.9671	0.9570	0.9443
19test	0.8742	0.7283	0.9742	0.9794	0.9659	0.9549
20test	0.8176	0.7461	0.9743	0.9581	0.9628	0.9356
Average	0.7795	0.7901	0.9706	0.9556	0.9537	0.9397

Table 2: Performance results on DRIVE data set and our new data set using STARE texton

To demonstrate that texton trained from one data set can be reused on the other data sets we train on data from STARE and test on images from DRIVE (D*) and also images collected at Manchester Eye Hospital (N*) Table 2 illustrates the corresponding sensitivity, specificity and accuracy for each test image. The results show that both D* and N* have competitive performance compare with the other proposed methods in Table 1.

4 Conclusion

In this paper, a novel texton-based segmentation method is proposed. A new filter bank MR11 was designed for vessel extraction considering the structural properties of retinal vessels. Experiments show that our proposed method outperforms some state of the art methods, while the performance compares well with the best published results on DRIVE and STARE datasets. On the STARE dataset, average specificity reaches 0.9643 with 0.7515 sensitivity, the accuracy is 0.9506. The terms of specificity, sensitivity and accuracy for the DRIVE dataset are 0.9831, 0.7167, and 0.9591 respectively. Meanwhile, our comparative results prove that once generated the unified textons can be applied on the other data sets for the purpose of vessel segmentation. This suggests that the textons are successfully capturing vessel texture and the framework for learning and selecting textons is robust. We believe that our proposed texton-based method demonstrates potential improvements and achieves more accurate segmentation results by optimizing the parameters of the filter bank, introducing a new filter (Gabor) and employing a sort process (post clustering) that finds the best combination of textons for our application.

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