Retinal Vessel Segmentation Based on Difference Image and K-Means Clustering

Temitope Mapayi\textsuperscript{1}, Serestina Viriri\textsuperscript{1} & Jules-Raymond Tapamo\textsuperscript{2}
\textsuperscript{1} School of Mathematics, Statistics & Computer Science, University of KwaZulu-Natal, Durban, South Africa.
\textsuperscript{2} School of Engineering, University of KwaZulu-Natal, Durban, South Africa.
Email: tmapayi@yahoo.com; \{viriris; tapamoj\}@ukzn.ac.za

Abstract—As retinopathies continue to be major causes of visual loss and blindness worldwide, early detection and management of these diseases will help achieve significant reduction of blindness cases. However, an efficient automatic retinal vessel segmentation approach remains a challenge. This paper presents study on the combination of difference image and K-means clustering for the segmentation of retinal vessels. K-means clustering combined with difference image based on median filter addressed the segmentation of large and thinner retinal vessels as well as the reduction of false detection around the border of the optic disc. This paper also shows that K-means combined with difference image based on median filter out-performs difference image based on mean filter and difference image based on Gaussian filter while combined with K-means for retinal vessel network segmentation. The good performance of the difference image based on median filter is however attributed to the good edge-preserving property of median filter. A maximum average accuracy of 0.9556 and a maximum average sensitivity of 0.7581 were achieved on DRIVE database. While compared with the previously used techniques on DRIVE database, the proposed technique yields higher mean sensitivity and mean accuracy rates in the same range of very good specificity.

Keywords: Difference Image, K-Means Clustering, Retinal Vessel, Segmentation

I. INTRODUCTION

Digital retinal photography, and image analysis in ophthalmology have been lately identified to be helpful in the diagnosis and progress monitoring of several diseases like diabetic retinopathy (DR), retinopathy of prematurity (ROP) and cardiovascular diseases [7],[8]. Although DR and ROP continues to be major causes of visual loss and blindness worldwide, early detection and management of these diseases will help achieve significant reduction of blindness cases [5] [29]. Ophthalmologists, with the help of detected vessel network, concentrate on retinal vessel feature analysis during the diagnosis of the diseases. Manual detection and analysis of the retinal vessels in the fundus images has been a very tedious and time consuming task that requires trained and skilled personnel who are often scarce [23] [25]. However, with the help of automatic vasculature segmentation and analysis, ophthalmologist can now diagnose and efficiently manage the diseases [12].

Several retinal vessel segmentation techniques have been published in literatures. Chaudhuri et al. [3] applied otsu thresholding technique to a two-dimensional matched filter response (MFR) image. It however achieved low detection of retinal vessels. Martinez-Peretz et al. [13] combined scale space analysis and region growing for the segmentation of retinal vessel network. This technique was however unable to segment the thin vessels. Zana et al. [32] employed mathematical morphology for the detection of retinal vessel network.

Akram and Khan [2] enhanced the vascular pattern using 2-D Gabor wavelet. A multi-layered thresholding approach that applied different threshold values iteratively was further used to generate gray level segmented image. Cornforth et al. [4] applied wavelet analysis, supervised classifier probabilities and adaptive threshold procedures, as well as morphology-based techniques. Jiang and Mojon [6] implemented an adaptive local thresholding model utilizing a verification-based multi-threshold probing scheme. This technique has poor detection of the thinner vessels and some unconnected vascular structures. Mapayi et al. [10] implemented an adaptive thresholding technique utilizing different types of local homogeneity information for retinal vessel segmentation. Qin et al. [16] combined multi-scale analysis based on Gabor filters, scale multiplication, and region based thresholding for the segmentation of retinal vessels.


proposed gradient based approach and level set technique for the segmentation of retinal vessels. The technique implemented in [24] was however unable to detect the thinner vessels. Vlachos et al. [26] implemented a multi-scale line-tracking combined with a morphological post-processing technique. Wang et al. [27] proposed multi-wavelet kernels and multi-scale hierarchical decomposition for the segmentation of retinal vessels. Xiao et al. [30] proposed a Bayesian method with spatial constraint for the segmentation of retinal vessels. Yin et al. [31] implemented a probabilistic tracking-based method for vessel segmentation.

Agung et al. [1] implemented vector quantization coding on retinal images using k-means and fuzzy c-means clustering algorithms. Lupascu and Tegolo [9] trained a self-organizing map (SOM) on retinal images. The map was further divided into two classes using k-means clustering technique. The entire image is fed into SOM again and the class of the best matching unit on SOM is assigned to each pixel. A post-processing technique based on hill climbing strategy on connected components was used to detect the vessel network. Ramaswamy et al. [17] implemented k-means and fuzzy c-means clustering techniques for the classification of exudates and non-exudates in retinal images. Saffarzadeh et al. [20] implemented a preprocessing phase based on k-means followed by the use of multi-scale line operators for the detection of retinal vessel network. With the help of K-means, the visibility of the vessels was enhanced and the impact of bright lesions of reduced. The retinal vessels were finally detected using the line detection operator in three scales. Wen et al. [28] investigated the use of k-means clustering to improve the detection of retinal vessels by reducing the color space. The result obtained in [28] was however not satisfactory.

Although, much has been achieved in the previous works, the performances obtained from literatures suggest the need for further work to address the segmentation of large and thinner retinal vessels as well as the reduction of false detection around the border of the optic disc. This paper presents an investigatory study on the combination of difference image and K-means clustering for retinal vessel network segmentation.

The rest of this paper is organized as follows. Section two describes the methods and techniques used in this paper. Section three explains the experimental setup, results and discussion, while the conclusion is drawn in section four.

II. METHODS AND TECHNIQUES

Generally, noise due to uneven illumination and contrast in retinal images affects the quality of the vessel segmentation. Since efficient vessel network detection is a very important step needed in ophthalmology for reliable retinal vessel characterization, an efficient segmentation technique that performs the segmentation of large and thin vessels in a timely efficient manner is highly needed. The green component of the coloured retinal image is used for segmentation since it provides the best vessel-background contrast [15]. A detailed description of the vessel segmentation approach investigated in this paper is given in five steps; 1) Extraction of the green channel of the coloured fundus image. 2) Convolution of the green channel of the retinal image using different filtering techniques. 3) Generating the difference image. 4) Segmentation of the retinal vessels from the generated difference image using K-means clustering. 5) Implementation of a post-processing phase that combines median filter and morphological opening for the removal of misclassification.

A. Filtering Techniques

The green channel of the retinal image is enhanced using different filtering techniques. Linear filters such as mean filter and Gaussian filter are used for smoothing images. Although these filters reduce image noise, they are however weak at preserving edges in an image. Non-linear filter, particularly median filter, is efficient at removing image noise as well as preserving edge information in images. It is however worth noting that the selected filter window sizes should not be too large in order to efficiently manage the noise due to illumination variation conditions of the retinal image. It is also important to carefully select window sizes that have sufficient data points for good enhancement. For the purpose of investigation in this paper, mean, Gaussian and median filters are considered for the convolution of the retinal image. The convolution of the retinal image is described as:

$$U = H \bigotimes V$$

(1)

hence

$$U(x,y) = \sum_{(a,b) \in H(x-a,y-b) \in V} H(a,b) V(x-a, y-b)$$

(2)

where $U$ is the convolved retinal image, $V$ is the green channel of the retinal image and the convolution mask $H$ is any of the filtering technique under investigation.

B. Difference Image

A difference image is generated by subtracting the green channel of the coloured retinal image from the convolved retinal image. The difference image $D(x,y)$ is given below as:

$$D(x,y) = U(x,y) - V(x,y)$$

(3)

such that $D(x,y) = \{ D_o(x,y), D_v(x,y), D_n(x,y) \}$. where $D_o(x,y)$ is the difference image based on median filter (DIMDF), $D_v(x,y)$ is the difference image based on mean filter (DIMNF) and $D_n(x,y)$ is the difference image based on Gaussian filter (DIGF). A model that combines two possible difference images were also investigated. The combinations obtained are:

$$D_v^o = D_o(x,y) + D_v(x,y)$$

(4)

$$D_v^o = D_o(x,y) + D_v(x,y)$$

(5)

$$D_v^o = D_v(x,y) + D_v(x,y)$$

(6)
where $D_{\text{g}}^b$ is the combination of median filter and mean filter based difference images (DIMDMNF), $D_{\text{g}}^b$ is the combination of median filter and Gaussian filter based difference images (DIMDGF) and $D_{\text{g}}^b$ is the combination of mean filter and Gaussian filter based difference images (DIMNGF). The results obtained in equations (4) to (6) are normalized to the interval $[0, 255]$.

C. K-Means Clustering

K-means clustering is an unsupervised segmentation technique used in defining the natural group of pixels in an image. This is achieved by classifying input image data points into different classes through a set of distances computed using the image data points and centroids. K-means clustering technique is used for dividing n sample input data points of $X = \{x_1, x_2, ..., x_n\}$ into a group of k clusters. This is achieved by considering the similarities among the input points within the same cluster as well as the differences among the different clusters. Sum of squared errors is a very useful criterion considering the similarities among the input points within the same cluster.

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$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} ||x_j - \mu_i||^2$$

such that $\mu_i$ is the centroid of the $i^{th}$ cluster $S_i$, $\{i = 1, 2, ..., k\}$.

Algorithm 1 K-Means Clustering Algorithm

1: Using random intensity values, initialize the centroids $\mu_1, \mu_2, ..., \mu_k$
2: Each of the image data points is assigned to one of the k clusters using the minimum distance principle, that is

$$d_i = \min_j ||x^{(i)} - \mu_i||$$

3: A new centroid is computed for each cluster

$$\mu_i = 1/m \sum_{j=1}^{m} x_j$$

Given that $1 \leq m \leq k$
4: Repeat step 2 and step 3 until the centroids stop changing. In such a situation the clustering criterion

$$\sum_{i=1}^{k} \sum_{j=1}^{m} ||x_j - \mu_i||^2$$

converged. Given that $x_j \in S_i$, $\mu_i$ is the centroid of the $i^{th}$ cluster $S_i$.

The K-means clustering technique described in Algorithm 1 is used to segment the vessel network from the background tissue in the retinal images using the results generated from equations 3 to 6.

D. Post-Processing

Median filter and morphological opening are used in the post-processing phase for the removal of wrongly-detected vessel pixels. A 2x2 median filter is used to get rid of the noisy pixels in the image. A morphological opening is further used to remove the remaining noisy pixels to obtain the segmented vessel network.

III. Experimental Results and Discussion

Experiments were carried out using MATLAB 2010a on an Intel Core i5 2410M CPU, 2.30 GHz, 4GB of RAM. The proposed method was evaluated using the retinal images on the publicly available DRIVE database [18]. DRIVE database provides twenty testing set of retinal images captured with the use of Canon CR5 camera with 24-bit gray-scale resolution and a spatial resolution of 565 x 584 pixels. DRIVE database also provides twenty gold standard images as the ground truth of segmented vessels for the comparative performance evaluation of different vessel segmentation algorithms.

Empirically, we established that using window sizes 11 x 11, for mean and Gaussian filters, 15 x 15 for median filter and the value K=10 were effective for the detection of the vessel network. The average time taken to segment the vessel networks in each of the retinal image on DRIVE database ranges from 3.4 to 3.6 seconds.

The performance measures used are sensitivity, specificity and accuracy. The measures are described in the equations (12) - (14) below as:

$$Sensitivity = TP/(TP + FN)$$

$$Specificity = TN/(TN + FP)$$

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)$$

where TP = True Positive, TN = True Negative, FP = False Positive and FN = False Negative.

An event is said to be TP when a pixel is rightly segmented as a vessel and TN when rightly segmented as background. In related development, an event is said to be FN if a vessel-pixel is segmented to be a background, and a FP when a background pixel is segmented as a pixel in the vessel. Sensitivity measure indicates the ability of a segmentation technique to detect the pixels belonging to vessel while specificity measure indicates the ability of a segmentation technique to detect background pixels. The accuracy measure indicates the degree of conformity of the segmented retinal image to the ground truth.

Table 1 shows the performance of the various difference images combined with K-means clustering. K-means with DIMDF has the best segmentation performance while compared to K-means with DIMNF and K-means with DIGF. K-means with DIMDF has the best average accuracy rate 0.9556 with an average sensitivity rate of 0.7399. Fig. 1 also gives a visual description that compares the results obtained from vessels segmented using K-means with difference image based on each of the filters. DIMDF combined with K-means clustering detected majority of large and thin vessels, while a very few thinner vessels remain undetected. There are some false detection and other artefact around the border of the optic disc. The false detection around the border of the optic disc are however lesser on the segmented vessels using DIMDF with K-means but higher on DIMNF and DIGF while combined with K-means. This is however due to the fact that median filter preserves edge information of the vessels in the...
Fig. 1: (a) & (e) DRIVE Database Gold Standard. (b) & (f) Segmented Vessels Using K-Means With DIMDF. (c) & (g) Segmented Vessels Using K-Means With DIMNF. (d) & (h) Segmented Vessels Using K-Means With DIGF.

Fig. 2: (a) DRIVE Database Colored Fundus Image (b) DRIVE Database Gold Standard (c) Segmented Vessels Using K-Means With DIMDF (d) Segmented Vessels Using K-Means With DIMNGF (e) Segmented Vessels Using K-Means With DIMDGF (f) Segmented Vessels Using K-Means With DIMDMNF.
enhanced retinal image. In related development, DIMDMNF and DIMDGF while combined with K-means yielded higher average sensitivity rates of 0.7581 and 0.7518 respectively. The increase in sensitivity is as a result of the integration with DIMDF. DIMDF however has the highest average accuracy rate while compared to DIMDMNF, DIMDGF and DIMNGF while combined with K-means clustering. As shown in Fig. 2, majority of large and thin vessels are detected, a very few thinner vessels still remain undetected. The false detection around the border of the optic disc are higher on the results obtained by using DIMDMNF, DIMDGF and DIMNGF while combined with K-means clustering but lesser on the results obtained while using K-means combined with DIMDF. This is also responsible for the higher average accuracy rate achieved. Fig. 3 gives a visual description that compares the results obtained from a few different vessels segmentation techniques in literatures. It can be observed that Jiang & Mojon [6] was unable to segment the thin vessel. Although Martinez-Perez et al [13] has a better segmentation, it however has a very high false detection around the border of the optic disc and failed to segment the thin vessels. In related development, the segmented result obtained by Ricci and Perfetti [19] segmented the large and part of the thinner vessels but has a very high false detection around the border of the optic disc. The segmented vessels obtained in the proposed K-means combined with DIMDF improved by reducing the false detection around the border of the optic disc and also segmented both large and part of the thinner vessels.

The performance measures of the different previously proposed techniques on DRIVE database are also compared the proposed techniques in Table 1. The best performing combinations of the proposed approach gave higher average sensitivity and accuracy rates, while compared to the previous techniques. Although the work Ricci and Perfetti [19] yielded higher accuracy rate, it however did not specify its sensitivity rate.

IV. CONCLUSION

A study on the use of difference image and K-means clustering for the segmentation of retinal vessels was presented this paper. K-means clustering combined with difference image based on median filter addressed the segmentation of large and thinner retinal vessels as well as the reduction of false detection around the border of the optic disc. We also showed that K-means with difference image based on median filter out-performs difference image based on mean filter and difference image based on Gaussian filter while combined with K-means for the segmentation of retinal vessels. The reason for the good performance of median filter cannot be far fetched from the fact that it has a very good edge-preserving property. This paper also showed that an integration of difference images based on linear filtering approach with difference image based median filter, while combined with K-means clustering also produces a very good vessel segmentation performance. Furthermore, we showed that the proposed vessel segmentation technique that combines difference image with K-means clustering is time efficient and gives higher accuracy.

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Fig. 3: (a) Result obtained in Ricci and Perfetti [19] (b) Result obtained from the proposed K-means combined with DIMDF (c) Result obtained in Martinez-Perez et al. [13] (d) Result obtained by Jiang & Mojon [6].
average sensitivity, average accuracy and very good specificity rates while compared to the previous techniques on DRIVE database. In our future work, we shall characterize segmented retinal vessels using tortuosity measure.

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REFERENCES


