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Machine Learning Approach for Accurate Segmentation of Blood Vessels in Fundus Images

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***Abstract*— Blood vessel segmentation is the necessary basis while developing retinal screening systems since vessels serve as one of the main retinal attraction features. Medical diagnostics has been drastically improved by the introduction of digital imagery, primarily because of the powerful digital image processing tools. Digital retinal images are used for diagnostics of various diseases containing diabetes, hypertension, stroke, etc. Since Retinal blood vessels are vital for such diagnostics, the segmentation of retinal blood vessels is an important and active research area. This paper proposes an automated method for the identification of blood vessels in color images of the retina. For every image pixel, a feature vector is computed that utilize properties of scale and positioning selective Gabor filters. In this paper, we propose a Support Vector Machine based algorithm for retinal blood vessel classification by using chromaticity and image matting coefficients as features. In this paper, the proposed algorithm was tested on the standard benchmark retinal images from the DRIVE data set. Results were equated with available ground truth images and other approaches from literature and vessel segmentation were excellent in all cases.**

***Index Terms*— diabetic retinopathy; blood vessel extraction; peak detection; valley detection**

INTRODUCTION

Blood vessel appearance is a dynamic indicator in several diagnosis namely diabetic retinopathy, hypertension and arteriosclerosis. In this paper, the main focus is DR. Due to the increasing growth of interest in image processing especially in the medical field, automated extraction of the blood vessel for diabetic retinopathy's patient is proposed. Retinopathy is a general term, which refers to some type of non-incendiary harm to the eye in the retina. DR can lead to several abnormalities and the abnormalities are not connected to other structures on the retina are Micro Aneurysms (MA), Haemor Rhages (HR), Exudates (EX) and Cotton Wool Spots (CWS). These abnormalities present in the early stage of DR recognized as Non-Proliferative Diabetic Retinopathy (NPDR). Meanwhile, Proliferative Diabetic Retinopathy (PDR) is an advance stage of DR. In PDR, a new blood vessel may grow and the new vessels are abnormal and very fragile.

There are three (3) main methods that can be generally classified for blood vessel detection; window-based, classifier based and tracking based [1]. Kirbas and Quek [2] on the other hand they did a survey in the vessel extraction technique and algorithm.

In his paper, 6 categories are classified; pattern recognition techniques, model-based approaches, tracking-based approaches, artificial intelligence approaches, approaches based on neural networks, and tube-like object detection approaches. For the pattern recognition techniques, there are a few approaches such as multi-scale, skeleton-based, region growing and ridge-based. Meanwhile, for model-based approaches, three (3) subs categories have been classified; namely deformable models, parametric models and generalized cylinders approach. This paper utilized as mathematical morphology that can be categorized in pattern recognition based on Kirbas and Quek [2]. Reza et.al [3] proposed to employ the Quadtree method to detect the blood vessel in RGB using the RGB component. The proposed method obtained positive fraction as high as 0.77, which is comparable to the decision achieved through different techniques known.

Vallabha et.al [4] utilized to scale and orientation-selective Gabor filter banks. The recommended way is to classify the retinal image as a moderate or severe based on the output obtained by the Gabor filter. Localized adaptive thresholding and a multi-window Radon transform are used in discover the vascular framework in retinal images. The proposed method by [5, 6] utilized 20 images (10 normal and 10 abnormal) and the effect exhibited that a normal positive rate of 86.3% and the false positive rate is 3.9%. Meanwhile, Hoover et.al proposed to segment the vessel network with global and local features cooperatively [1]. Gaussian matched channel is used to find the middle focus and width of a vessel in its cross-sectional profile. Next, the expanded Kalman Filter is utilized for the optimal direct estimation of the following conceivable area focus. Afterword, a branching detection strategy is proposed to check the bifurcation [7]. Jiang and Mojon [8] proposes a local thresholding framework. The proposed method demonstrates a superior performance on normal compared to abnormal. Recently, Xu and Luo [9] also proposed to use adaptive thresholding and then extract the large connected component as the large vessels. The residue fragments are classified using Support Vector Machine (SVM). The average sensitivity obtained is over 77%. Sukkaew et.al [10] proposed Laplacian of Gaussian edge detector as a step on the second-order directional derivative identified by the location of the ship with zero crossings. Chaudhuri et.al proposed two (2) dimensional matched filters to detect the blood vessel [11].

RELATE WORKS

There are many segmentation techniques published in the literature. They can be divided into supervised and unsupervised methods.

Supervised techniques require initial information about segmented retinal blood vessels. The performance of the supervised methods is much better than unsupervised methods. However, getting the required information such as expert training sampling datasets for a supervised segmentation process can sometimes be difficult. The main disadvantage of the supervised method during vessel segmentation is the classification of vessels and the background pixels considered tedious. Niemeijer et al have developed the supervised classification of pixels for retinal segmentation. Each pixel of a green channel of the retinal images was used to generate the feature vector, and a k-NN classifier is used to drive the feature vector. Staal et al. developed the supervised segmentation method using the edge extraction method. Primitives in the form of line elements were generated from the ridge and feature vectors were used for each pixel for the classification process as vessels and background using the selection sequential entities ahead and k-NN. Soares et al. created feature vectors composed of pixel intensities with scaled responses from the two-dimensional Gabor wavelet transform on each pixel. The resulting feature vector was classified into the vessel and non-vessel pixels using a Bayesian classifier and Gaussian mixtures. Fraz et al. have developed the supervised segmentation method based on the ensemble classifier using bootstrapped decision trees for the extraction of retinal blood vessels. Lupascu et al. [12] presented a supervised method of extraction of retinal vessels using an Ada-Boost classifier. Ricci and Perfetti [13] have implemented two different methods of automated vessels segmentation, based on the detection of vessels line operators by the classification of the support vector machine. Cemal [14] has developed a hybrid method of extracting retinal blood vessels by combining Circular and Naive Bayes. The circular method is used to sample pixels along with the magnification of the circles centered on the current pixels. Then, after the classifier Naive Bayes, the pixel is classified as a ship or non-ship.

The unsupervised segmentation is an arduous task to achieve accurate segmentation of retinal blood vessels due to the pixel-based classification of vessels and non-vessels. Many unsupervised methods previously proposed are quick in the computation process, but they are not capable of correctly detecting vessels and non-vessels due to retinal network limitation of unconnected vessels of the fundus image. As a result, these methods make it possible to obtain less sensitivity and precision. Chaudhuri et al. [3] developed the unsupervised vessel extraction method based on the matched filter using the approximate intensity of the greyscale profiles of the cross-section of the retinal vessels along with the curve form of Gauss. But the detection sensitivity of vessels is very low. Hoover et al. [4] developed the retinal blood vessel extraction method using a thresholding technique combining local vessel characteristics and region-based features on the Matched Filter Response (MFR) image. Martinez-Perez et al. [15] applied a space-scale analysis with the growing region for the segmentation of retinal vessels. The novelty of this method is to detect large vessels.This method does not detect tiny vessels. Zana and Klein [16] have developed the mathematical morphological method for the retinal blood vessel segmentation, they have achieved a very good result, but the structure of the vascular network is not always connected. Jiang and Mojon [17] used an adaptive local thresholding model using a multi-threshold approach and verification based on segment blood vessels in the retina. The technique envisioned in [17] was confronted with the limits of some unconnected vascular structures and the inability to detect the thinnest vessels. Vlachos and Dermatas [18] implemented their method.

By combining a multi-scale line tracking procedure and a morphological post-treatment for the segmentation of retinal vessels. But this technique also did not detect small vessels. The method developed by Wang et al. [19] combined the multi-wavelet and multi-scale hierarchical decomposition for the segmentation of retinal vessels. The method has reached the highest precision, and its calculation is expensive. Mendonca and Campilho [20] implemented the process by combining differential filters for center line extraction with operators for the detection of the retinal vessel network. The good performance is achieved, but the calculation is expensive. Xiao et al. [21] produced a spatially constrained Bayesian technique with the level defined for the segmentation of retinal vessels.

Tolias and Panas [22] used a fuzzy C-means algorithm to spot blood vessels in the retinal segment from images of angiograms images, but the technique did not segment the thinner vessels because of their low contrast against the background. Kande et al. [23] combined the paired filter and a space-weighted fuzzy c-means for vessel extraction of retinal fundus images. But tiny vessels cannot be extracted by the low disparity of the vessels. Yang et al. [24] proposed a hybrid method combining Fuzzy C-Mean and morphological operations. But the algorithm has been tested by visual comparison, by visual calculation of the sensitivity level of the detection of small vessels that cannot be calculated. In this research paper, a new supervised method is implemented, taking into account the above-mentioned limitation, to detect tiny blood vessels and perform better than the existing supervised methods.

THE PROPOSED METHOD

In this paper, a novel automatic blood vessel segmentation method is performed in color retinal fundus images. A vessel enhancement operation including various matched filters such as Gabor, Gauss, and Frangi is utilized after a preprocessing step. After that, a top-hat transform is applied for further enhancement of blood vessels. Then, the binary vessel map is obtained by using hard and soft clustering methods (Fuzzy C-means and K-means). Finally, falsely isolated pixels are removed as a post-processing step. The block diagram of this method is shown in Figure 1.

The STARE database consists of 20 fundus images (ten of them have various pathological cases). The images have been captured with a Top Con TRV-50 digital fundus camera at 35° Field Of View (FOV). The dimensions of the images are 700 × 605 pixels with 24 bits (8 bits per each color channel). All images in this database have corresponding manually segmented versions in which the pixels are labelled as vessel or non-vessel by two observers. The second observer labelled thin vessels much more. We use the images labelled by the first observe as ground truth data for performance evaluation. There are no Region of Interest (ROI) masks in this database

Secondly, the DRIVE database contains 40 images (seven of them have various pathological cases). The images have been captured with a Canon CR5 nonmydriatic 3CCD digital retinal fundus camera at a 45° field of view (FOV). The dimensions of the images are 768 × 584 pixels with 24 bits (8 bits per each color channel). All images in this database also have corresponding manually segmented versions. The images have been divided into two parts as training and testing. Each part contains 20 images. We use testing images for performance evaluation. There are corresponding Region Of Interest (ROI) masks in this database.

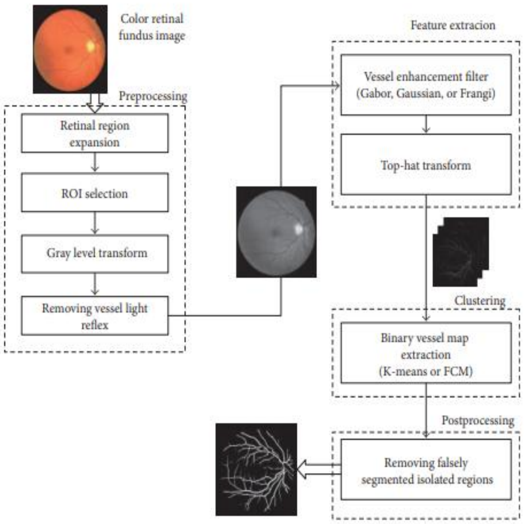

Figure 1: The block diagram of the method

Preprocessing

The retinal region is circular even though fundus images are rectangular. Therefore, retinal region masks must be utilized to select the region of interest in fundus images. There are corresponding masks in the DRIVE database whereas many databases such as STARE do not contain any mask to select the retinal region. Thus, the retinal region mask might be segmented automatically for a general framework.

The input image to select the retinal region, but some pixels belonging to vessels or dark regions in the retina could be segmented as out of the retina. In this study, we use not only a basic threshold but also additional criteria which are different values between color channels (red, green, and blue) and the average RGB values. we calculate the average of RGB values. Then, the sum of the difference between RGB values is calculated and we decided the mask value according to

$$\mathrm{mask}(x,y) = \begin{cases} 1, & \mathrm{avg}(R,G,B) < T_1,\ D < T_2 \\ 0, & \text{otherwise,} \end{cases}$$

where D = R − G + R − B + G − B . In 1, T1 and T2 are the threshold values and determined empirically. For the best performance, T1 is taken as 40 and T2 is taken as 50. When we use only a basic threshold, the average accuracy is calculated as 99.04% and the standard deviation is 1.01% and some vessel pixels are classified as mask pixels. When we use the criteria mentioned above, the average accuracy is calculated as 99.78% and the standard deviation is 0.25% and none of the vessel pixels are classified as mask pixels.

Many vessel enhancement approaches utilize convolution operation with symmetric structured elements. Consequently, unwanted artifacts might occur on the border of the retina. An expansion of ROI is applied to solve this problem, after the selection of the retinal region. The pixel set on the border of the retina is obtained and, then, a pixel reflection operation is performed according to border pixels by taking the symmetric values. Here, the reflection size is set as 6 for the best results.

Gray Level Conversion

There are various gray level conversion methods to obtain an intensity image. Some methods might use only one of the color channels such as green channels whereas others use the sum of multiplication such as the color channels with special coefficients. The sum of the color coefficients must be 1 (cr+ cg+ cb= 1) to get intensity as normalized. The general formula is given in

$$I = c_r * R + c_g * G + c_b * B,$$

where I is the intensity value, R, G, and B are the intensities of red, green, and blue color channels, respectively, and cx values are the color coefficients. In many retinal vessel segmentation methods, the green channel of the color image is taken as gray-level intensity because the maximum contrast is obtained with this channel (cr= 0, cg= 1, and cb= 0). Some other methods could use the average of RGB values (cr= 1/3, cg= 1/3, and cb= 1/3) or special gray level transform coefficients such as cr= 0.3, cg = 0.59, and cb= 0.11. In this paper, we selected the color channel coefficients as cr= 0.1, cg= 0.7, and cb= 0.2 by using a training set from image databases (STARE and DRIVE). Some details could be found in our previously done study [29].

Vessel Light Reflex Removal

Since retinal blood vessels have lower brightness compared to the retina, their intensities are darker than other retinal pixels but a brighter strip could be observed in the center of some retinal blood vessels. To remove this effect, a gray level morphological opening operation is applied to the intensity image with a three-pixel diameter disc [10].

Feature Extraction

Two-dimensional Gaussian based matched filtering was firstly used for retinal blood vessel segmentation by Chaudhuri et al. [1]. Since the retinal cross-sectional vessel profile is similar to a Gaussian shape, a two-dimensional Gaussian-based matching template could be utilized for the best approximation to the blood vessels. The mathematical equation of a 2D Gaussian template could be described as

$$G(x, y) = -\exp\left(\frac{x^2 + y^2}{2\sigma^2}\right),$$

where σ is the standard deviation of the Gaussian function and could be assumed as the scale of the Gaussian filter. x and y parameters are rotated to span all possible orientations. In this paper, an angular resolution has taken as 15° in a similar manner mentioned in the Gabor filter.

K-Means Clustering

Pixel Intensity features 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 = {x1, x2, ..., xn} 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. The sum of squared errors is a very useful criterion measure for clustering. Given k clusters, the sum of squared errors is computed as:

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

such that μi is the centroid of i th cluster Si, {i = 1, 2, ... k.}.

Algorithm 1:K-Means Clustering Algorithm

1: Using random intensity values, initialize the centroids μ1, μ2, ..., μk

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

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

4: Repeat step 2 and step 3 until the centroids stop changing.

The K-means clustering technique described in Algorithm 1 is used to segment the vessel network from the background tissue in the retinal images

Support Vector Machine

This section describes the proposed retinal blood vessel segmentation method based on the SVM algorithm. The first step in the detection of blood vessels is feature extraction from RGB retinal image. During the extraction of the blood vessels, only the green channel of RGB images is used since it makes the best contrast between the blood vessels and the background.

Input data of SVM are characteristics that are obtained by digital image processing [8] of the retinal image. Features that are suggested are:

a) Inverse green channel,

b) Continual green channel.

When calculating the Inverse green channel, it is important to note that the green channel is scaled in the range [0,1]. The Inverse green channel value is calculated when subtracting scaled green channel value from 1.

The Continual line detector is obtained when we move through the image with a window and calculate the average value of the line for 12 different orientations. The length of the line is 15 pixels [4]. The line is rotated at an angle of 15˚ relative to the central pixel of the window. The optimal size of the square window is found to be 15x15 [4]. After the line with the largest average gray level is found, the direction of pixels is determined by the direction of the strongest lines (one of the twelve angles). The continual line detector is calculated by summing pixels that are on the line with a maximum average value in the mask 15x15, but only in the case when the direction of pixels corresponds to the direction of the central pixel. The final value of the second feature was obtained when the average value of the sum was subtracted from the average value of the whole mask. The second feature of one of the images from the DRIVE database.

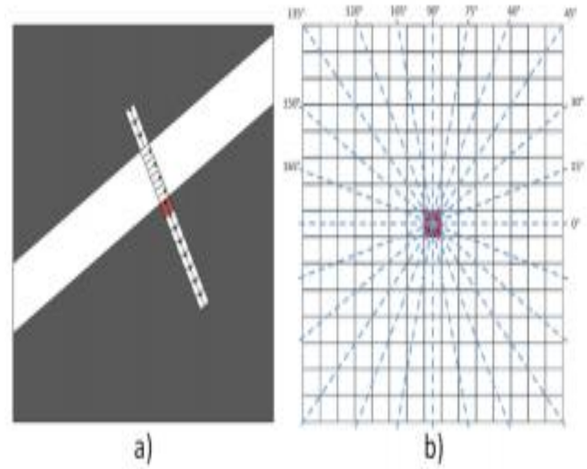

Fig. 2 a) Basic line detector (blood vessel shown in white). b) Twelve orientations to determine the strongest line.

After the features were calculated, SVM is trained. During the training of SVM, the Gaussian kernel [3] was used. The optimal parameters, that are determined on the training set, are 0.1=C and 3. We used 20000 pixels= σ (1000 pixels per image) that are randomly chosen from the training set. Classification performance is then evaluated on the 20 images of the test set.

RESULTS

In this study, we applied our method on two publicly available online databases known as STARE and DRIVE. As we mentioned in Section 2.1, the STARE database has 20 fundus images and the DRIVE database has 40 fundus images that were divided into two subsets: the training image set (20 images) and the testing set (the remaining 20 images). We tested our method on all 60 images and utilized the second observer's labelling as ground truth data for comparison. Firstly, some secondary metrics such as true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are calculated as follows:

(i) True positive (TP): the count of vessel pixels correctly classified as a vessel

(ii) True negative (TN): the count of background pixels correctly classified as background

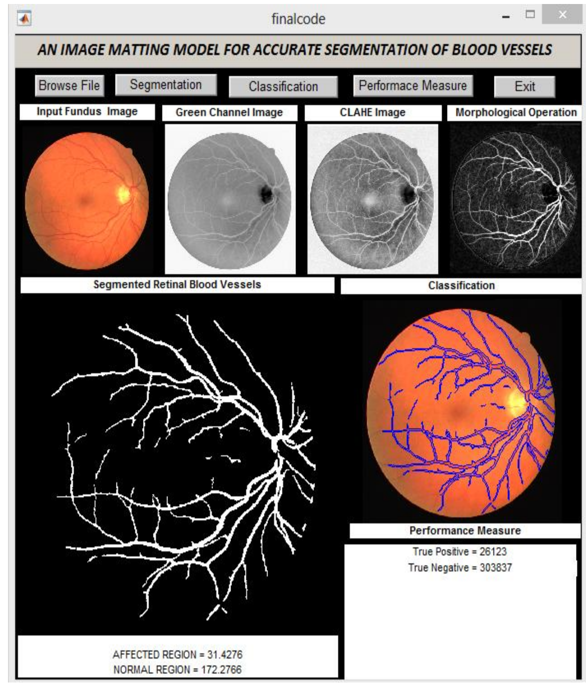

Fig. 3: Result obtained from the proposed K-means combined with SVM

The obtained experimental results are compared to the other methods and binary vessel image is illustrated in Figure 3. It could be observed that the illustrated binary vessel network is given in is good and has a satisfactory result for visual inspection. The performance metrics are calculated whether in the ROI or the whole image. It means that the mask image for the retina is considered or not. NA indicates that any information is not available. The proposed method performs 95.94% of accuracy on STARE and 95.71% of accuracy on DRIVE databases where the whole image pixels are considered. The accuracy values obtained by using the mask image (in ROI) are also given for a fair comparison. The results measured in ROI are 94.37% and 94.00% on STARE and DRIVE databases, respectively. The proposed approach in this paper outperforms better performance than most of the other studies with the specificity (the specificity on the DRIVE database exceeds all of the other studies). The obtained specificity results are 98.16% and 99.05% on STARE and DRIVE databases, respectively

The SVM based approach proposed by Sayyada et al. [35]showed the best accuracy as well which marked SVM the best method because of its technical orthogonal transformation, which converts the set of observation of possibly variables that have mutual relationship into a set of values of linearly variables that do not have a mutual relationship.

CONCLUSION

Retinal blood vessel segmentation approaches could be divided into two categories as rule-based and machine learning methods. We have presented a novel approach based on several blood vessel enhancement and unsupervised classification (clustering) methods within the latter. A preprocessing operation is performed to obtain a retinal mask instead of using manually labelled one followed by vessel enhancement filtering. Then, we used two clustering schemas as hard clustering (K-means) and soft clustering (Fuzzy C-means) for pixel classification. To test the proposed system, two publicly available retinal fundus image databases (STARE and DRIVE) are used and experimental results are given as sensitivity, specificity, and accuracy. One of the main contributions of the proposed segmentation method is taking cluster size c as three instead of two which we have seen mostly in literature. As given in tables above, higher accuracy values are obtained by increasing cluster size c. In traditional clustering methods, the cluster size had been taken as two. However, this paper reveals that taking cluster size as three could provide better performance in any case. The second important feature of our method is using automatically segmented masks for the retinal region (region of interest) instead of manually labelled ones. This provides us to produce an automatic solution for a general-purpose without any need to manually label a retinal mask. The next significant feature of the developed system is using an unsupervised classification approach which provides us to segment retinal blood vessels without any training operation. Additionally, the Gabor filter followed by K-means clustering is a new combination of methods and relatively better than the others. In this paper, a system for retinal blood vessel segmentation is trained with the help of features obtained by digital image processing and SVM. The green channel of the RGB image is used because it provides the biggest contrast between the blood vessels and the background. Features matrix is contained in two columns: the green channel and continual line detector. In future work, we aim to study the measurements of segmented retinal vessels and integrate them with our vessel segmentation method.

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