

Performance analysis of screening diabetic retinopathy

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This study presents a new method for screening Diabetic Retinopathy (DR), is the leading ophthalmic pathological cause of blindness among people of working age in developed countries. The first manifestations of DR are tiny capillary dilations known as Microaneurysms (MA) and Exudates. It may provide an early indication of the risk of the Type –I Diabetes. The various features of the images of the Retinal Vessels are used to indicate the different MA's and Exudates disease processes. Neural Networks and k-means clustering provide significant benefits in medical research. This Proposed work deals DR with Segmentation and Classification algorithms for the analysis of Retina images. This effectiveness and robustness, together with its simplicity make this Optimized analysis for being integrated into a complete screening system for early DR detection. It proposes an Optimized Soft Computing technique approach for screening the Diabetic retinopathy.

Keywords: Diabetic retinopathy (DR), Exudates, Microaneurysms (MA), Neural Networks.

Introduction

Diabetic retinopathy (DR) is a micro vascular complication that may occur in patients with diabetes. The occurrence of diabetic retinopathy will result in the disturbance of visual capability, and can eventually leads to blindness. The longer a person has untreated diabetes, the higher his chance of developing diabetic retinopathy. Along with diabetes, high blood sugar levels in long periods can affect small blood vessels¹ in the retina, There will be changes in the strength of the walls of the vessels. This can result in small hemorrhages in the retina. The weakened walls will also cause micro aneurysms that leak fluid into the retina.

In retinal fundus image, micro aneurysms appear as small reddish dots. Diabetic retinopathy becomes symptomatic in its later stage. In the first stage, diabetic patients may not be aware of having infected by the disease. Early detection of diabetic retinopathy plays a major role in the success of such disease treatment, so that the worse case can be anticipated.

Diagnosis of this disease² is usually conducted by the ophthalmologist by employing retinal images of patients. By using a fundus camera, an ophthalmologist can obtain retinal fundus images from patients to be

diagnosed. From the image, symptoms will be identified manually by an ophthalmologist, therefore the more patients to be diagnosed; the more time will be needed. Detecting micro aneurysms as the first clinical symptom of diabetic retinopathy will give a contribution in helping ophthalmologists to identify patients that need to be treated. We're currently carrying on a research to develop methods so that the detection of micro aneurysms from retinal images can be done by a computer-aided diagnosis system.

Normal structures of retina are the optic disk², macula, and blood vessels. If a person suffers diabetic retinopathy, micro aneurysms may occur in a patient's retinal image as tiny reddish dots. The risk of visual disturbance is increased when the occurrence of micro aneurysms is close to the macula. In our proposed system, normal structures are to be detected first. Detected optic disk is useful to locate the center of macula, while blood vessels detection is needed to avoid false positives, for there are property similarities between blood vessels and micro aneurysms. The detected microaneurysms will be highlighted in the image to ease the diagnosis by ophthalmologist. Further analysis can be done by counting the number of detected micro aneurysms and measuring each one's distance to the macula. Other properties of micro aneurysms will be studied to develop an analysis module. The proposed diagnosis system can ease the

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process by highlighting the occurring micro aneurysms and giving information about the properties³. This paper describes our preliminary design of the Diabetic Retinopathy Screening System. We also present results of our current segmentation of blood vessels structures progress in various fundus retinal images. We obtained necessary data from Leading Eye Center, and consulted the result with an ophthalmologist.

Review of Related Research

Rumano A. Simandjunta *et al*⁴ have proposed an automatic method to detect blood vessels from low-contrast digital images of retinopathy patients. Contrast enhancement preprocessing was employed using four features, such as intensity, standard deviation on intensity, hue and a number of edge pixels, and they were removed to supply as input parameters to coarse segmentation. The detection results were validated by analyzing with expert ophthalmologists' hand-drawn ground-truths. Martins *and others*⁵ have discussed and analyzed a automated system to detect early diagnosis of diabetic retinopathy. They used entropic thresholding and wavelet transform for detecting and segmenting the blood vessels from the retinal images. Martinez *et al.* have also proposed a method based upon multi scale feature extraction. The local maxima over scales of the gradient magnitude and the maximum principal curvature of the Hessian tensor were used in a multiple pass region growing procedure. Growth progressively segmented the blood vessels by using both feature and spatial information. Gardner *et al*⁶ proposed a back propagation multilayer neural network (NN) for vascular tree segmentation. The NN was then fed with the values of these pixel windows for classifying each pixel into vessel or not. Soares *et al*⁷ used a Gaussian mixture model Bayesian classifier. Multi scale analysis was performed on the image by using the Gabor wavelet transform. The gray-level of the inverted green channel and the maximum Gabor transform response over angles at four different scales were considered as pixel features. Finally, Ricci and Pefetti *et al*⁸ used a support vector machine (SVM) for pixel classification as vessel or non vessel. They used two orthogonal line detectors along with the gray-level of the target pixel to construct the feature vector.

Vessel segmentation method

This paper proposes a new supervised approach for blood vessel detection based on a NN for pixel classification. The necessary feature vector is computed

from preprocessed retinal images in the neighborhood of the pixel under consideration. The following process stages may be identified: 1) original fundus image preprocessing for gray-level homogenization and blood vessel enhancement, 2) feature extraction for pixel numerical representation, 3) application of a classifier to label the pixel as vessel or non vessel, and 4) post processing for filling pixel gaps in detected blood vessels and removing falsely-detected isolated vessel pixels.

Input images are monochrome and obtained by extracting the green band from original RGB retinal images. The green channel provides the best vessel-background contrast of the RGB-representation, while the red channel is the brightest color channel and has low contrast, and the blue one offers poor dynamic range⁹. Thus, blood containing elements in the retinal layer (such as vessels) are best represented and reach higher contrast in the green channel¹⁰. All parameters described below were set by experiments carried out on DRIVE images with the aim of contributing the best segmentation performance on this database (performance was evaluated in terms of average accuracy).

Preprocessing

Color fundus images often show important lighting variations, poor contrast and noise. In order to reduce these imperfections and generate images more suitable for extracting the pixel features demanded in the classification step, a preprocessing comprising the following steps is applied: 1) vessel central light reflex removal, 2) background homogenization, and 3) vessel enhancement. Next, a description of the procedure, illustrated through its application to a DRIVE database fundus image is detailed.

1) *Vessel Central Light Reflex Removal*: Since retinal blood vessels have lower reflectance when compared to other retinal surfaces, they appear darker than the background. Although the typical vessel cross-sectional gray-level profile can be approximated by a Gaussian shaped curve (inner vessel pixels are darker than the outermost ones), some blood vessels include a light streak¹¹ (known as a light reflex) which runs down the central length of the blood vessel. To remove this brighter strip¹, the green plane of the image is filtered by applying a morphological opening using a three-pixel diameter disc, defined in a square grid by using eight-connexity, as structuring element. Disc diameter was fixed to the possible minimum value to reduce the risk of merging close vessels.

Background homogenization

Fundus images often contain background intensity variation due to non-uniform illumination. Consequently, background pixels may have different intensity for the same image and, although their gray-levels are usually higher than those of vessel pixels (in relation to green channel images), the intensity values of some background pixels is comparable to that of brighter vessel pixels. Since the feature vector used to represent a pixel in the classification stage is formed by gray-scale values, this effect may worsen the performance of the vessel segmentation methodology. With the purpose of removing these background lightening variations, a shade-corrected image¹² is accomplished from a background estimate. This image is the result of a filtering operation with a large arithmetic mean kernel, as described below.

Firstly, a 3×3 mean filter is applied to smooth occasional salt-and-pepper noise. Further noise smoothing is performed by convolving the resultant image with a Gaussian kernel of dimensions 9×9 and a mean=0 and variance= 1.8^2 . Secondly, a background image, is produced by applying a 69×69 mean filter. By applying this filter in final stage, the border line pixels are become high intensity values. The Difference Image can be produces as

$$D = I_\gamma - I_B; \quad \dots(1)$$

Where, I_γ = Vessel reflex removed image; I_B = Background Image;

The 'D' may contain -ve pixel values also. Hence, normalization is used to acquire the pixel values between 0 to 255. Normalized Difference Image is called as "Shade Corrected Image".

The Homogenized Image (I_H) can be produced using the following procedure

- Take Histogram of I_{SC}
- Take the pixel (or) intensity value of the largest Histogram count.

$$\text{i.e., } g_{\text{input-max}} = \max(\text{count});$$

$$g_{\text{input}} = I_{SC}$$

Then the Homogenized image can be produced as,

$$I_H = 0; \text{ if } g < 0; \quad \dots(2)$$

$$I_H = 255; \text{ if } g > 255; \quad \dots(3)$$

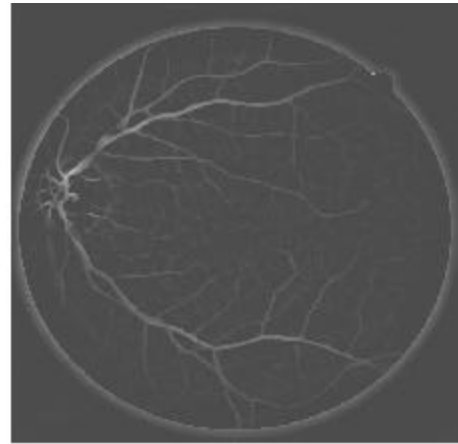


Fig.1—Vessel Enhanced Image

$$I_H = g; \text{ if otherwise; } \quad \dots(4)$$

$$\text{Where, } g = g_{\text{input}} + 128 - g_{\text{input-max}} \quad \dots(5)$$

Vessel Enhancement

The final preprocessing step consists on generating a new vessel-enhanced image, (Fig 1) which proves more suitable for further extraction of moment invariants- based features. Vessel enhancement is performed by estimating the complementary image of the homogenized image I_H , I_H^C , and subsequently applying the morphological Top-Hat transformation as follows,

$$I_{VE} = I_H^C - \gamma(I_H^C) \quad \dots(6)$$

Thus, while bright retinal structures are removed (i.e., optic disc, possible presence of exudates or reflection artifacts), the darker structures remaining after the opening operation become enhanced (i.e., blood vessels, fovea, possible presence of microaneurysms or hemorrhages).

Feature Extraction

The aim of the feature extraction stage is pixel characterization by means of a feature vector, a pixel representation in terms of some quantifiable measurements which may be easily used in the classification stage to decide whether pixels belong to a real blood vessel or not. In this paper, the following sets of features were selected:

- *Gray-level-based features*: features based on the differences between the gray-level in the candidate pixel and a statistical value representative of its surroundings.

- *Moment invariants-based features*: features based on moment invariants for describing small image regions formed by the gray-scale values of a window centered on the represented pixels.

Since blood vessels are always darker than their surroundings, features based on describing gray-level variation in the surroundings of candidate pixels seem a good choice. A set of gray-level-based descriptors¹³ taking this information into account was derived from homogenized images considering only a small pixel region centered on the described pixel. These features are:

$$F_1(x,y) = I_H(x,y) - \min \{I_H(s,t)\} \quad \dots (7)$$

$$F_2(x,y) = \max \{I_H(s,t)\} - I_H(x,y) \quad \dots (8)$$

$$F_3(x,y) = I_H(x,y) - \text{mean} \{I_H(s,t)\} \quad \dots (9)$$

$$F_4(x,y) = \text{std}\{I_H(s,t)\} \quad \dots (10)$$

$$F_5(x,y) = I_H(x,y) \quad \dots (11)$$

The vasculature in retinal images is known to be piecewise linear and can be approximated by many connected line segments. For detecting these quasi-linear shapes, which are not all equally wide and may be oriented at any angle, shape descriptors invariant to translation, rotation and scale change may play an important role. Within this context, moment invariants proposed by Hu¹⁴ provide an attractive solution and are included in the feature vector.

Microaneurysms and Optic Disc Segmentation

Microaneuysms Candidate Extraction

Microaneurysms are small blood clots which occur due to capillary burst. They are the hardest to detect in retinopathic images. Microaneurysms are treated as holes in retinal images (i.e. small dark blobs surrounded by brighter regions). Blood vessels can also appear as noise in the microaneurysm detection as they have similar color and contrast to the clots. A general methodology for candidate MAs segmentation, originally proposed by Spencer et al. In this paper a matched filter is used to enhance the contrast between background and microaneurysms in I_{lesion} . This system consists in finding the Vessel segmented image I_{vas} which is subtracted from the original image I_{org} .

$$I_{\text{lesion}} = I_{\text{org}} - I_{\text{vas}} \quad \dots (12)$$

The resulting image (I_{lesion}) contains mainly nonelongated structures including candidate

microaneurysms. The matched filter is a 2-D Gaussian with $s = 1$ pixel and size of 11x11 pixels. The resulting filtered image I_{filt} is threshold to produce a binary image I_{bin} . The threshold is fixed at a certain level above the modal value of the image. A region growing procedure is used to grow back the original pathologies in original retinal image I_{org} from the binary objects in I_{bin} . The darkest pixel under each of the binary objects provides the starting point. The background image I_{bg} obtained in the preprocessing step can be used to find the threshold t for the region growing procedure as follows:

$$t = i_{\text{seed}} - x(i_{\text{seed}} - I_{\text{bg}}) \quad \dots (13)$$

where i_{seed} is the intensity at the starting position, i.e., the pixel under the binary object with the lowest gray value, and I_{bg} is the intensity of the same pixel in the background image and $x \in [0, 1]$. We use $x = 0.5$ as suggested by Spencer et al. The region growing algorithm starts in the seed pixel and stops when no more connected pixels below the threshold can be found.

Optic disc Segmentation

The detection of the optic disk in fundus images is a very important task because of its similarity in brightness, color and contrast to the exudates. It invariably appears in exudates detection results and hence there is a need to mask it out. Moreover, the optic disk is an important retinal feature and can be used for registration of retinal images. It can also be used to diagnose other diseases like Glaucoma. In this paper, the optic disc can be segmented by using the following stages;

(a). *Stage 1: Elimination of blood vessels structures*:

- Detection of blood vessels by means of morphological operation.
- Elimination of blood vessels by means of anisotropic diffusion.

(b). *Stage 2: Construction of coarse optic disc contour*:

*Collection of contour point candidates.

*Filtering outlier contour point by means of spline interpolation.

However, the existence of blood vessels, especially within the optic disc region may cause misdetection of pixels belonging to blood vessels as optic disc contour points. Therefore, the blood vessels structures within optic disc region are eliminated using anisotropic diffusion.

Table 1—Exudates detection results of retinal images on Drive1 database

Database	S_e	S_p	P_{pv}	N_{pv}	Acc	SuccessRate
DRIVE1(images 1to 100)	0.91	0.89	0.98	0.95	0.96	0.938
DRIVE2(images 1 to 100)	0.97	0.90	0.96	0.98	0.97	0.956

Table 2—Comparison of Several Classifier Performances on Blood Vessel Segmentation

Classifier	Database	S_e	S_p	P_{pv}	N_{pv}	Acc	SuccessRate
K-means	DRIVE1	0.6014	0.8402	0.3608	0.9583	0.8187	0.7158
Fuzzy C-Means	DRIVE1	0.7218	0.7612	0.5618	0.7634	0.6910	0.6998
Neural Network(proposed)	DRIVE1	0.7291	0.9177	0.4298	0.9755	0.9029	0.791

Table 3—Comparison of Several Methodology Performances on Blood Vessels Segmentation

Methodology	Database	S_e	S_p	P_{pv}	N_{pv}	Acc	SuccessRate
Maximal Entropic Thresholding	DRIVE1	0.7689	0.5909	0.6756	0.6865	0.789	0.7021
Gabor wavelet	DRIVE1	0.5439	0.6345	0.8714	0.7643	0.6907	0.7009
Proposed method	DRIVE1	0.7291	0.9177	0.4298	0.9755	0.9029	0.791

After several iterations of the anisotropic diffusion process, small features and blood vessels structures are effectively removed while optic disc contour is still well preserved. This facilitates the task of obtaining the true optic disc contour.

Exudates detection

The chief cause of exudates is proteins and lipids getting leaked from the bloodstream into the retina through damaged blood vessels. In retinal images, exudates exhibits as hard white or yellowish localized regions with varying sizes, shapes and locations. Exudates are a major indicator of diabetic retinopathy that can possibly be quantified automatically. This paper focuses on automatic detection of diabetic retinopathy exudates in color fundus retinal images.

Neural Network Design

A multilayer feed forward network, consisting of an input layer, three hidden layers and an output layer, is adopted in this paper. The input layer is composed by a number of neurons equal to the dimension of the feature vector (nine neurons)¹⁴⁻¹⁵. Regarding the hidden layers, several topologies with different numbers of neurons were tested. A number of three hidden layers, each containing 15 neurons, provided optimal NN configuration. The output layer contains a single neuron and is attached, as the remainder units, to a nonlinear logistic sigmoid activation function, so its output ranges between 0 and 1. This choice was grounded on the fact of interpreting NN output as posterior probabilities. Two classification stages can be distinguished: a design stage,

in which the NN configuration is decided and the NN is trained, and an application stage, in which the trained NN is used to classify each pixel as vessel or non-vessel to obtain a vessel binary image. The maximum number of 100 retinal images from DRIVE database are trained and tested by Neural networks classifier.

Experimental Results

Performance Measures

In order to quantify the algorithmic performance of the proposed method on a fundus image, the resulting segmentation is compared to its corresponding gold-standard image. This image 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. Thus, automated vessel segmentation performance can be assessed. The Performance of Proposed Retinal Image Screening for Diabetic Retinopathy can be analyzed with the following Parameters:

- Sensitivity(S_e)
- Specificity (S_p)
- Positive predictive value(P_{pv})
- Negative predictive value(N_{pv})
- Accuracy(Acc)

They can be calculated as:

$$Se = TP / (TP + FN) \quad \dots(14)$$

$$Sp = TN / (TN + FP) \quad \dots(15)$$

$$Ppv = TP / (TP + FP) \quad \dots(16)$$

$$Npv = TN / (TN + FN) \quad \dots(17)$$

$$Acc = (TP + TN) / (TP + FN + TN + FP) \quad \dots(18)$$

These are listed in Table 1-3.

The entire algorithm was run on the DRIVE database and results for optic disk localization, exudate detection and Blood vessel detection were obtained. The Matlab code takes 10 seconds per image on an average to run on a 2.1 GHz Intel Pentium Dual Core machine with 1GB RAM.

Conclusion

Previous methods for screening Diabetic retinopathy in retinal images can be classified into rule-based and supervised methods. This research proposes a method based on a NN scheme for pixel classification, being the feature vector representing each pixel composed of gray-level, moment invariants-based features, Haralick's texture and Law's texture features. The results are encouraging and these methods contribute to our overall goal of development of a system for the automated screening of Diabetic Retinopathy. Thus this method can help the ophthalmologist to detect the blood vessels, MAs and Exudates detection and Optic disc segmentation in the screening process.

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