Automatic Exudates Detection in Retinal Images Using Efficient Integrated Approaches

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Abstract—Diabetic Retinopathy with exudates causes a major problem in human visualization and becomes a cause of blindness to diabetic patients. In addition, the numbers of diabetic retinopathy patients are increasing while the numbers of doctors are not easily increased in the same proportion. This circumstance causes a heavy work load for doctors. In the past, the medical image processing research has shown that simply getting a second opinion can significantly help physician’s diagnosis. This research proposes a method to detect exudates from diabetic retinopathy images. The early exudates detection of diabetic retinopathy patients will reduce seriousness in diabetic retinopathy. The proposed method for detecting exudates consists of 5 major steps as follows: 1) To improve the quality of images by using the contrast limited adaptive histogram equalization (CLAHE) 2) To apply the object attribute thresholding algorithm (OAT) for non-retinal object removal, 3) To implement Frangi’s algorithm based on Hessian filtering for blood vessel detection 4) To detect the retinal optic disc by applying the combination between multi-resolution analysis and Hough transform and 5) To classify exudates in the remaining region with algorithms of hierarchical fuzzy-c-mean clustering. The performance of the proposed method is evaluated on DIARETDB, which is the retinal image database of the Lappeenranta University of Technology, where the performance is good enough for exudates detection.

I. INTRODUCTION

Diabetes is an important chronic disease influence to the subsistence, family and economic circumstance of patients. It can be cured if it is found in its first phase. The statistics of World Health Organization (WHO) [1] specify the prevalence of diabetes worldwide for the year 2000 and estimated for 2030 are 171 and 366 million peoples. Haft of the people who have diabetes don’t know it. Globally, of diabetic patients who have had the disease for more than 15 years, 2% become blind and 10% have severe visual impairment and 32% have abnormal retinopathy.

Diabetic retinopathy (DR) is caused by the abnormality of blood vessels which is a vascular complication. It makes the diabetes patients have a 25xhigher risk of blindness higher than the people without diabetes. 40% of the patients who are more than 40 years old have DR. Four stages of DR division exist: 1) Mild Nonproliferative Retinopathy, microaneurysms materialize and perhaps hemorrhage or hard exudates. 2) Moderate Nonproliferative Retinopathy, cotton wool spots arise because the retina cultivation is deprived. 3) Severe Nonproliferative Retinopathy. Blood supply restrains many regions of retinal and several blood vessels are restricted 4) Proliferative Retinopathy. The vitreous gel flows into the eye. The blood vessels do not permit adequate blood flow. It leads to vision loss and even blindness. [2][page 14-15]

Exudates are indicators for diabetic macular edema diagnosis, and appear in a yellowish or white color which is caused by the fat and proteins from microaneurysms. They vary in size, shape, and location. Often they are present in stripes or clusters or circinate the surrounding area of microaneurysms. [3]

Many researchers developed exudate detection procedures. A. Osareh, and others [7] proposed fuzzy a c-means clustering method to segment the region of retinal image into exudates and nonexudates dataset and applied the multi-layer perceptron neural network to classify exudate location. P. Aravindhan and P. N. Jebraian Sargunar [8] presented the exudate detection which clusters the noise removed fundus image into two classes by using fuzzy c-means algorithm and implemented advanced modified cross point number method with a window size parameter of 7x7 for the exudate identification part. W. Sae-Tang, and others [11] implemented the non-uniform illumination background subtraction. The eliminated data contains optic disk, fovea, blood vessels, and lesions. Level-set evolution is used to detect the exudates on the remaining foreground of the image. M. Esmaeili, and others [10] applied the curvelet transform on the bright candidate lesions to distinguish between exudates and the

In this paper propose exudates detection method contain 5 major steps. Images quality improvement is applied by the contrast limited adaptive histogram equalization (CLAHE) and use the object attribute thresholding algorithm (OAT) for background removal. Blood vessel evaluation and extraction is performed by Frangi’s algorithm based on Hessian filtering. The combination between multi-resolution analysis and Hough transform use to detect retinal optic disc. And also classify exudates in the remaining region with algorithms of hierarchical fuzzy-c-mean clustering.

The proposed method is functioned on 16 images from DIARETDB, standard diabetic retinopathy database of the Lappeenranta University of Technology, which the images were captured with few 50 degree field-of-view digital fundus cameras.

II. MATERIAL AND PROPOSED METHOD

Our method is implemented in the green channel of a retinal image as shows in figure 3. Brightness level of blood vessel, optic disk, and vitreous humor quite difference clearly. This section consists of 5 chapters corresponding to our ensemble learning method. Section 2.A improves image quality with contrast limited adaptive histogram (CLAHE). Section 2.B eliminates the background from retina by using an object attribute thresholding algorithm and a region extension method. Section 2.C masks blood vessels with Frangi’s vessel filtering. Section 2.D finds the optic disc by performing the combination between multi-resolution analysis and Hough transform and Section 2.E detects exudate in the residual area with algorithms of hierarchical fuzzy-c-mean clustering.

A. Image Quality Enhancement

- CLAHE

CLAHE is a generalization of adaptive histogram equalization (AHE). It was originally developed for enhancement of low-contrast medical images. CLAHE differs from ordinary AHE in the amplification limiting by clipping the histogram. Sharp field edges can be maintained by selective enhancement within the field boundaries.

The CLAHE is applied to the green channel of retinal images (I_{G}) to intensify edges between each objects. The improvement is a necessary preparation process for enhancing performance of all of the following algorithms.

B. Background elimination

- Object attribute thresholding (OAT)

OAT is binarization algorithm that executes Otsu’s algorithm recursively in which all iterations separate the image data into a bi-modal histogram based on optimum variance and chooses a class to perform in the next iteration. The function operates until it meets the appropriate class of histogram. The result is a binary image (I_{OAT}). However, it is not a finished background mask. It still has a little remaining background close to the retinal image.

- Region extension

The region extension algorithm is applied to the I_{OAT} image to cover the neighboring region of the binary image using a blurring method for growing the region and a gradient procedure to detect differences between each pixel and its neighbor.

To eliminate the edge between the background and the retinal image, the consolidation between blurring and gradient algorithms on the I_{OAT} image construct the extension area and combines the region and interested area in the I_{OAT} image to construct a new background masking image (I_{BGM}).

C. Blood vessel detection

- Histogram Equalization (HE)

HE is a popular method which increases the dynamic range of the gray-level in a low-contrast image to cover a full range of gray-levels, based on cumulative distribution probability.

To maximize the blood vessel detection performance, the high contrast between vessels and other objects can lower the complexity of the operation.

- Frangi’s filter[4]

The algorithm for vessel structure detection using eigenvalues and hessian matrix calculated by differentiation is:

\[ \mathcal{H}_d(x) = \frac{\partial^2 I_d}{\partial x^2} = I(x) \cdot \frac{\partial^2 g_d(x)}{\partial x^2} \]

where I, g, and \( \sigma \) are original image, Gaussian function, and standard deviation respectively. The ensemble of second derivative extracts eigenvalues \( \lambda_1 \leq \lambda_2 \leq \lambda_3 \) and directions \( (u_1, u_2, u_3) \).

\[ V_p(x) = \begin{cases} 0 & \text{if } \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ (1 - \exp \left( \frac{R_{p_1}}{2 \alpha^2} \right)) \exp \left( \frac{R_{p_2}}{2 \beta^2} \right) (1 - \exp \left( \frac{S^2}{2 \Sigma^2} \right)) & \end{cases} \]

where \( \alpha, \beta, c \) are filtering sensitivity parameters for individual geometrical structure evaluation comprised of tube-like and plate-like \( (R_A) \), blob-like \( (R_B) \), and background \( (R_A) \) parts as follows in the equation below.

\[ R_A = \frac{\lambda_1}{\lambda_2} = \frac{\lambda_1 |}{\lambda_2 \lambda_3} \quad R_B = \frac{\lambda_1 |}{\lambda_2 \lambda_3} \quad S = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2} \]
The vesselness appraisement is accommodated for the filter result at various scales by taking the optimal response.

\[ v_r(x) = \max_{\text{max}(r)} v_P(x) \]

The operation produces the blood vessel binary mask (I_{VE}) to allocate all vessel areas.

D. **Optic disc finding**

To increase the speed of computing, all procedures of this section use low resolution input images.

- Sobel edge detection

Technically the Sobel operator is a discrete differentiation operator for calculation of an approximation of the gradient of the image intensity function in which the result is either the corresponding gradient vector or the norm of this vector. The pixel result image is convolution of Sobel kernel using the following equation:

\[ |g| = \sqrt{a^2 + b^2} \]

where \( a \) and \( b \) are coordinate of the mask position when the central position is defined to be \((0,0)\).

To construct the edge mask, convert three color channels to gray scale and apply the process to all channels. However, the process ignores the vessel region in I_{VD} image. The three binary image results are assembled to produce a single edge mask (I_{E}) with a XOR operation.

- Hough transform

A Hough transform can detect lines, circles and other structures if their parametric equation is known which can give robust detection under noise and partial occlusion. The circle detection uses the equation:

\[ (x-a)^2 + (y-b)^2 = r^2 \]

where \( a \) and \( b \) are the coordinate of the central position of the circle and \( r \) is radius.

After the localization of the circles centers, the process continue by accumulating in a one-dimensional space which coordinate is the radius of concentric circles with the given centre. The summation of edge for the points along the circle is calculated:

\[ R(r) = \sum_{P \in \text{circle}(r)} E(P) \]

where \( E \) is edge evaluation operation and \( P \) is an interesting point.

The operation was implemented to find the optic disc which has a circle characteristic. I_{E} image is an edge binary result of the expected result and can be adjusted appropriately for each situation.

To define the interested area in an expected exudate region, the operation does not cover the space of I_{BGM}, I_{VE}, and I_{OD} which are already restricted. Edges in binary mask result have a high possibility for actual exudate location.

- Morphology closing operation

The algorithm is normally applied to a binary image. Generally, it is used to remove noise or small objects. Single structuring element dilates the image to enlarge the boundaries of the foreground area and erodes it by the same structured element.

\[ A \odot B = (A \oplus B) \ominus B \]

where \( \oplus \) and \( \ominus \) denote the dilation and erosion, respectively. The set \( A \) is a binary image and is processed by structured element \( B \).

Nonetheless, the result of Kirsch’s templates still has a small object that is encompassed by the bright region. This step’s point is to fully fill the small objects to cover the exudate expected regions. Disk-shaped structuring element, which size is 2, is defined.

- Median filter

The noise reducing technique is implemented extensively. The concept is assignment of each pixel by the median calculated value of their neighborhoods.

- Hierarchical fuzzy c-means clustering[6]

The fuzzy c-means clustering is a basis of many classification algorithms. Fuzzy c-means algorithm allows elements to belong to more than one cluster. The method predefines the \( N \), parameter of group number by 2, which is set \( R_M \). Each iteration of process will random value, estimate the membership of group, and calculate each group centroid for changing value in \( R_N \) until it is too low distance of value movement. It will increase \( N \) parameter by 1 and process until the memberships of some group is low in \( R_M \). \( R_{M-1} \) is proper set of cluster.

The remaining regions still have both exudates and vitreous humor location. The clustering applies to define the real exudates areas which are the brightest class.

III. **Result**

The general retinal Image is composed of background (black space), blood vessel, optic disc, and retina. The main idea of the proposed method is object’s detection from their characteristic criteria. The exudate can be classified from the remaining area, the retina region. For the experiment design, green channel images are used to evaluate the ensemble technique. It can present the best gray-level distinction compared with other color channels. To improve the object’s contrast, in Figure 4. (a) shows the obvious objects characteristic by CLAHE procedure effects all subsequent algorithms.

Figure 4. (b) shows the OAT result (I_{OAT}) can identify the background region, the large area and it has low variance. It also over detects the blood vessel location where the gray
level is close. Some effects occur from the previous image improvement steps, CLAHE makes the thin darkness area within a bright location gray level limner. Anyway, the characteristic of exudates are bright regions, it means it has no more effective significance for the main objective detection. But the binary mask result still is not covering the background area enough because between the retina and background have some reflective light remains. Region extension carries out the masking to solve the problem area. The combination of I_{OAT} and region extension constructs the background binary mask I_{BGM}.

To detect the blood vessel in the residual area, deploy the global image improvement in the image. The enhancement without background shows the better contrast of objects which contributes the high performance of blood vessel detection algorithm which presents the detail clearly. Frangi’s filter based on geometrical structure evaluation can determine the vesselness location. The object mask consolidation shows in figure 5. (b).

For the optic disc detection, the method adapts the multi-resolution analysis to increase the speed of operation. The image is resized to a low resolution and convoluted it by Sobel kernel to construct the edge binary image. The convolution result presents the circle edge around the optic disc area. Although it is not a smooth circle, it is enough for the detection. The Hough transform algorithm proceeds to find the region of the circle object. It has a high accuracy for the optic disc identification. Within the retina object, usually there is only one circle object. After locating the optic disc region, the circle area is reconstructed to apply to the original resolution image. The result of optic disc detection show in the figure 6.

After the object detection (I_{BGM}+I_{VE}+I_{O}) any main objects are already created to be the binary mask. The remaining areas may include retina, exudate, and other objects. For the finding of the abnormal objects start from the Kirsch's Template convolutions which construct the edge binary image (I_{KT}). Morphology closed operation is implemented in the I_{KT} to fill the noise-like spaces within the masking regions. The result covers both the exudate and edge of blood vessel areas. Nonetheless, the mask structures of both objects are quite different since the objects similar to the thin line have a high tendency of being the edge of blood vessel and almost exudate areas related to the circle structure. To eliminate blood vessel edge in the mask, the median filtering is applied. The binary image still has some noises and the expected exudate areas are larger than the actual exudate regions. The mask is already scoped to the exudate areas and remaining small non-exudate region. Hierarchical fuzzy c-means clustering is used to identify the class of exudate with the assumption that the brightest class is the actual exudate region.

Fig. 4. (a) is result of CLAHE, (b) OAT binary image that is extended the region and show the output in (c) and (d) is a combination of (b) and (c).

Fig. 5. (a) is result of HE process from the remaining area of I_{BGM} and Frangi’s Vessel Filtering conduce to (b) I_{VE}.

Fig. 6. (a) represent the operated image of Sobel kernel in the low resolution and (b) is a detected area by Hough transform which expected optic disc location

Fig. 7. The result image of continuous process (a-d) are Kirsch's Templates convoluted image, morphology closed operation, median filtering output, and the Hierarchical fuzzy c-means clustering group which is expected exudate area sequentially.
IV. DISCUSSION

In the experimental result, it includes some vessel regions in OAT step, but it is dark area and no exudates location which is brighter. The fundus images are assumed that optic disc is rather brighter vitreous humor, which have high level of transition region. The exudates classification step, is assumed that remaining areas have only exudate and some vitreous humor region which can result a better performance than various remaining location.

V. CONCLUSIONS

The algorithm was developed to detect exudates in retinal images based on the ensemble methods. All digital retinal images are taken from the benchmarking database of the Lappeenranta University. The proposed method for exudates detecting includes 5 major processes which are the enhancement and object classifications. The image improvement using contrast limited adaptive histogram equalization presents the gray-levels distribution to accelerate the objects detecting steps. The determining of object regions begins with the background region identification by object attribute thresholding which overlays all background and some blood vessel regions. Using Hessian filtering in the Frangi’s algorithm shows the capability of detecting blood vessels. The circle structure detection of Hough transform is implemented to determine the retinal optic disc with the multi-resolution analysis and can improve time efficiency. In the remaining area are included actual exudate space and other regions. Hierarchical fuzzy-c-mean clustering is applied to classify the exudates by the assumption that the brightest class is an actual exudate region. The method contributes the result that is sufficient for exudates detecting.

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Fig. 8. (a) is the original image and (b) is the final result of automatic exudates detection covers the actual exudate regions.

REFERENCES


