Detection of Exudates from Digital Fundus Images of Diabetic Retinopathy Patients

Diyabetik Retinopati Hastalarına Ait Sayısal Göz Dibi Görüntülerinden Eksüdaların Tespiti

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Abstract

Diabetes is a condition where the body does not produce enough insulin to convert sugar to energy, leading to a build up of sugar in the blood. This leads to a number of problems, including diabetic retinopathy. Diabetic retinopathy is a complication of diabetes that causes damage to the blood vessels of the retina that allowing you to see fine detail. It causes progressive damage to the retina. This paper proposes a simple yet an efficient approach for automatic detection of the exudates of the Diabetic Retinopathy. The detection of exudates of diabetic retinopathy is composed of eight steps: 1. RGB to gray conversion. 2. Moving mean to 0.5 3. Max Filter 4. Threshold specification 5. Optic disk removal 6. Remove of objects which is not exudates 7. Thresholding original image using the specified exudate regions 8. Computing statistical measures.

Özetçe


1. Introduction

Diabetic retinopathy is a progressive damage of the blood vessels in the retina of patients who have diabetes. Early recognition can arrest or reverse the expansion of the disease and keep from blindness. Diabetic retinopathy first shows itself slowly over the years as background retinopathy, which is the early stage of diabetic retinopathy. At this early stage, tiny blood spots appear on the retina. Increasing retinopathy develops from background retinopathy and is responsible for most of the visual loss in diabetics. In this condition, new blood vessels improve on the surface of the retina. These immature blood vessels tend to burst and bleed into the cavity of the eye. Scar tissue can also form from the ruptured blood vessels and can contract and pull on the retina, causing vision loss. One of the methods to diagnose DR is processing of digital fundus images. They are the visual digital images which are the appearance of a patient's retina, the retinal vasculature and the optic disk. The acquisition of fundus images is easy to perform. Therefore they are adapted for large scale screening purposes. Computer-aided detection and diagnosis of DR with retinal fundus images significantly lessens the burden of the implementation of a large scale screening of the diabetic patients. Recent years have seen the development of methods for the accurate detection of exudates by considering them individually and in a collective way. We mention here some of these works on automated detection of DR. Non linear diffusion segmentation is used to segment out the exudates by K.Narasimhan et al [1]. The segmentation of exudates using fuzzy c-means clustering algorithm is done by Akara et al [2].
Also, color normalization and local contrast enhancement followed by fuzzy C-means clustering and neural networks were used by Osareh et al. [3]. Gardner et al. proposed an automatic detection of diabetic retinopathy using an artificial neural network. The exudates are identified from grey level images by Gardner et al. [4]. In [5] a new hybrid classifier as an ensemble of Gaussian mixture model and support vector machine is proposed for exudate detection by M.U.Akram et al. As for mathematical morphology based exudate detection methods, vessels and optic disk are removed first, then mathematical morphology operators are performed to obtain the exudates. Sopharak et al.[6] used a closing operator and reconstruction operators together with thresholding to remove the optic disk and main vessels, then discriminate the exudate pixels according to the local variation due to exudate pixels have high contrast to its surrounding pixels. Retinal fundus image analysis currently attracts lots of attention from both computer science field and ophthalmology. Its aim is to develop computational tools which will assist quantification and visualization of the anatomical structures and lesions. It includes vessels analysis, optic disk analysis, macular analysis, micro-aneurysms detection and exudate detection. In this paper, we review the existing works on exudate detection since our work mainly focus on bright lesions which are exudates. Much work has been performed for exudate detection based on variety of techniques. Most techniques mentioned earlier worked on dilated pupils in which the exudates and other retinal features are clearly visible. Based on experimental work reported in previous work, good quality images with larger fields are required. The retinal images must be clear enough to show retinal detail.

2. Materials and Method

Digital Fundus image processing currently develop from computer science field. The method presented here can be schematically described by means of the block diagram of figure 1.

![Block diagram of proposed method.](image)

2.1. Materials

In this study we tested our algorithm on forty diabetic retinopathy fundus images which have similar characteristics. These fundus images were taken from 20 females and 20 males who have exudates as a cause of Diabetic Retinopathy. They were collected from the Ankara Maya Göz Hospital. All the results of our study have been approved by ophthalmologists Dr. Burcu Harç Kaya and Dr. Fariba Cafernejad from the Ankara Maya Göz Hospital, Turkey. All images were acquired using Topcon TRC-50EX fundus camera at 35 degree field of view. The camera were subjectively equalized for calibration, luminance and contrast before recording. The bit depth of images is 24-bit color and scaled to 1840x1224 pixels. The resolution of images are 96 dpi in horizontal and vertical dimensions. In some cases, due to the retinal surface difference, the images will have different appearance. Although some changes have been in visual features, the appearances of the fundus images were natural and bare. The method of the study was realized by using Matlab R2015b.

2.2. Methods

In this part, the methods used are summarized; the definitions and specifications of the methods are recalled. The block diagram of the approach is provide in figure 1. In the following, we describe the steps of the algorithm.

1. RGB image is converted to gray image. Y channel of NTSC color space is computed from RGB image (equation 1). And scaled to [0,1] range. A sample fundus image converted to gray scale is given in figure 2.

   \[ Y = 0.2989 \cdot R + 0.5870 \cdot G + 0.1140 \cdot B \]  

2. The field of view (pupil) of the fundus image is extracted. The region is specified by thresholding the image. The pixels with brightness higher than 0.1 is considered field of...
of view. If more than two connected components distinct regions are obtained by thresholding the biggest connected component (region) is regarded field of view. Next the mean brightness (value) in the field of view \( Y \) is moved to 0.5. The following linear transformation (equation 2) is employed.

\[
I = -\frac{1}{2m-2} Y + \frac{2m-1}{2m-2}
\]  \( (2) \)

3. Using 21x21 size overlapping window (20 samples overlap in horizontal and vertical directions) max filter (equation 3) is applied.

\[
y(m,n) = \max_{i,j} I(n+i, m+j), i,j = -5, ..., 5. \quad (3)
\]

For the image in figure 3, the max filter output is as follows.

![Max filter output](image)

4. A polygonal line consists of three line segments is fitted to cumulative histogram of image \( y \). The cumulative histogram is given by

\[
c(k) = \frac{\text{number of pixels} \leq k}{\text{total number of pixels}},
\]

\[k = (0, 1, ..., 255)/255. \quad (4)\]

A polygonal curve denoted by \( g(k) = P(a_1, a_2, a_3, a_4; k) \) is fitted to the cumulative histogram. Here, \( a_n, a_{n+1} \) are initial and end point of \( n \)-th line segment respectively. The unknown points are optimized such that mean square of error

\[
e(k) = c(k) - g(k) \text{ is minimum:}
\]

\[
\min_{a_1, a_2, a_3, a_4} \sum_{k=0}^{\text{size}} (c(k) - g(k))^2, \quad \text{subject to}
\]

\[
g(1) - g(0) = 1.
\]  \( (5) \)

The polygonal curve and cumulative histogram are shown in figure 4.

![Polygonal curve and cumulative histogram](image)

The threshold is then selected as

\[
\text{THR} = x(3) - 0.1 \left( x(3) - x(2) \right)
\]  \( (6) \)

where \( x(2) \) and \( x(3) \) are \( x \)-abscissa of points \( a_2 \) and \( a_3 \) respectively. The term \( 0.1 \left( x(3) - x(2) \right) \) is for taking into account that slope at \( a_3 \) does not change abruptly.

![Location of exudates](image)

5. After thresholding connected components are obtained and the component with highest area is considered optic disk (together with reflected light about the disk) and removed. Similarly the objects with major axis length greater than quarter of major axis length of the field of view are regarded as scattering of light from the border of the pupil.

6. To obtain final segmentation the pixels of the image \( I \) in the regions obtained are thresholded with the threshold obtained in step 4. With this threshold we detect the location of exudates which are shown in figure 5.

![Location of exudates](image)

7. Finally, we compute two statistical measures from the segmented image. Percentage of total exudates in the field of view = total area of exudates / pupil area. Percentage of biggest exudate = the highest exudate area / total area of exudates

3. Results

In this study, we propose a simple yet an efficient method on the fundus images with dispersed exudates. In figure 6
a good segmentation of the is reported. The method removes optic disk and finds exudates.

**Figure 6: Original image (left) and detected exudates (right)**

In some images, there is reflection at the boundaries of the fundus image due to camera light. This reflection effect success of exudate detection because these light reflections may be regarded exudates by the algorithm. The proposed algorithm also eliminates these reflected areas. The fundus image and its detected exudates given in figure 7 is a demonstration of this capacity.

**Figure 7: Original image (left) and detected exudates (right)**

The algorithm fails when exudates are not dispersed, the groping resulted by max filter is higher than the optic disk and gives bad results when the exudates are bigger than the optic disk diameter or major axis length of the reflected light at boundaries. Figure 8 shows an example of this situation.

**Figure 8: Original image (left) and detected exudates (right)**

### 4. Conclusion & Future Work

With this paper, diabetic retinopathy exudates were detected. It is experimentally shown that our model performs well on the fundus images with dispersed exudates. Finally We tested the method on several color fundus images to assess the performance of our approach. We conclude that the presented method can assist ophthalmologists to specify exudates and help to overcome the problem of contrast, incorrect illumination and noise while examining the fundus images. Additionally it may also support specialist for monitoring the progression of disease and aid for a better treatment plan. Our algorithm generally perform well but when the exudates (their groping by the algorithm) are bigger than the optic disk, it cannot remove it because we do not use a disk removal technique for just removing optic disk. Simply a segmented region, after max filtering, with the biggest area is removed. We will also apply special technique for removing optic disk. Our future attempt will be detection of optic disk before the algorithm is applied for specifying exudates. Using negative of the gray image it may be possible to detect micro-aneurysms by applying this algorithms with some modifications. In addition, detection of the lesions at earlier stages is still an open problem.

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## 6. References


