

Detection of Red Lesions For Diabetic Retinopathy In Telemedicine Context

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Abstract— In this paper we present the Red Lesion Detection for diabetic retinopathy in telemedicine context. The method used in this in this paper is the process of morphological image flooding. The development of an automatic telemedicine system for computer-aided screening and grading of diabetic retinopathy depends on reliable detection of retinal lesions in fundus images. Signs of DR include red lesions such as microaneurysms and intraretinal hemorrhages, and white lesions, such as exudates and cottonwool spots. This paper concerns only the red lesions, which are among the first unequivocal signs of DR. Therefore, their detection is critical for a prescreening system.

Keywords— Diabetic retinopathy, fundus IMAGING, lesion detection, retina, screening.

I. INTRODUCTION

Diabetic Retinopathy (DR) is also known as diabetic eye disease that will affect retina. It can eventually cause blindness. The severity of DR ranges from non-proliferative and pre-proliferative to more severely proliferative DR, in which the abnormal growth of new vessels occurs. Total or partial vision loss can occur through a vitreous hemorrhage or retinal detachment, and central vision loss can occur through retinal vessel leakage and subsequent macular edema.

II. RELATED WORK

With the increasing prevalence of diabetes and the aging population, it is expected that, in 2025, 333 millions diabetic patients worldwide will require retinal examination each year [4]. Considering the limited number of ophthalmologists, there is an urgent need for automation in the screening process in order to cover the large diabetic population while reducing the clinical burden on retina specialists.

Automation can be achieved at two levels: first, in detecting cases with DR, and, second, in grading these cases. Indeed, the identification of the severity level, through DR grading, allows more appropriate and consistent referral to treatment centers [5].

Several methods have been developed for the automatic detection of red lesions in color fundus images. Most of them [6]–[15] focus solely on the detection of MAs. Because of their fairly uniform circular shape and limited size range, MAs can be detected using morphological operations

such as diameter closing [11] and top-hat transformation using a linear structuring element at various orientations [6]–[10].

The goal here is to distinguish MAs from elongated structures. Another approach is to use a priori shape knowledge and to perform a convolution with a double ring filter [13] or through template matching with multiscale Gaussian kernels [12],[14], [15].

Retinal HEs are the result of MAs starting to leak into the retinal layers, indicating a more severe level of DR. According to the most common DR severity scale [5].

HEs come in different types, such as "dot", "blot" and "flame" [16]. Dot HEs and MAs are difficult to distinguish from one another on fundus images, thus dot HEs are usually referred to as MAs. A flame HE corresponds to blood leaking into the nerve fiber layer. Its shape, more elongated, follows the structure of the nerve fibers. A blot HE corresponds to blood leaking deeper in the retinal layer.

It appears larger than a dot HE, and its borders are irregular, leading to various shapes.

Fig. 1 shows examples of these lesions types.

A common methodology adopted in the literature for combined MA and HE detection consists in identifying all dark-colored structures in the image, mainly through a thresholding, combined with adapted preprocessing [16], [17], and then in removing the vessels from the resulting set of candidates.

Vessel detection is performed using either a multilayer perceptron [16] or multiscale morphological closing [17]. Unfortunately, the major limitation to this approach is that most of the false positives at the vessel segmentation step are actually lesions.

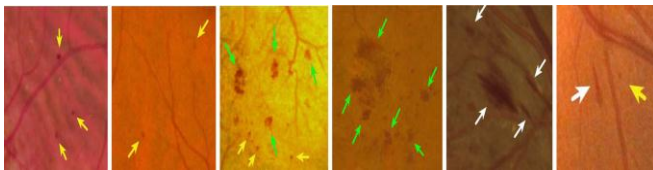


Fig. 1. Portions of different fundus images with red lesions. The yellow, green and white arrows point respectively to MAs/dot HEs, blot HEs and flame HEs.

After their removal along with the detected vessels, these lesions are lost and not retrieved in subsequent processing.

III. METHODOLOGY

The proposed method takes as input a color fundus image together with the binary mask of its region of interest (ROI).

The ROI is the circular area surrounded by a black background. It outputs a probability color map for red lesion detection.

Step-I Image Acquisition

Image acquisition can be broadly defined as the action of retrieving image from some basis. The successive steps are

- A. Gray scale image
- B. Denoising
- C. Contrast Enhancement

A. Gray Scale Image

Gray scale or gray scale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information.

The intensity of a pixel is expressed within a given range between a minimum and a maximum. This range is represented in an abstract way as a range from 0 (total absence, black) and 1 (total presence, white), with any fractional values in between.

B. Denoising

Noise is any undesirable signal. at each pixel in an image we have a neighborhood around that particular point, evaluate the values of all the pixels in the neighborhood according to the steps and then replace the original pixel's value with one based on the analysis performed on the pixels in the neighborhood.

The neighborhood, moves successively over every pixel in the image, repeating the process. A median filter does a very good job at reducing the noise in image.

C. Contrast Enhancement

Contrast is an important factor in any subjective evaluation of image quality.

Firstly, HE transforms the histogram of the input image into a uniform histogram by distributing the entire range of gray levels uniformly over the histogram of an image, with a mean value that is in the middle of gray level range.

Secondly, histogram equalization performs the enhancement based on the global content of the image. The following figure shows the output of Image acquisition

Step-II Image Segmentation

Image segmentation is the process of partition the input image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation which used to find objects and margins (lines, curves, etc.) in an images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

There are two steps involved in segmentation of medical image in digital image processing. They are

- A. Morphological Operation
- B. Thresholding Method

In this paper morphological operations are used in post processing mainly as a filter. Its fundamental operations are Boundary pixels and low frequency pixels are eliminated from image. Then difference image was generated. There are two operations performed in morphological process.

They are

1. Erosion
2. Dilation.

Erosion: It was originally defined for binary images, later being extended to gray scale images, and subsequently to complete lattices.

Dilation: The dilation is applied to binary images, but it can work on grayscale images also. The basic effect of the operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels.

Thresholding the simplest method of image segmentation. Set a threshold value over gray scale image,

binary images can be created. After, Thresholding is employed to segment red lesions in retinal images. Thresholding makes

it possible to highlight pixels in an image. Thresholding can be applied to gray scale images or color images.

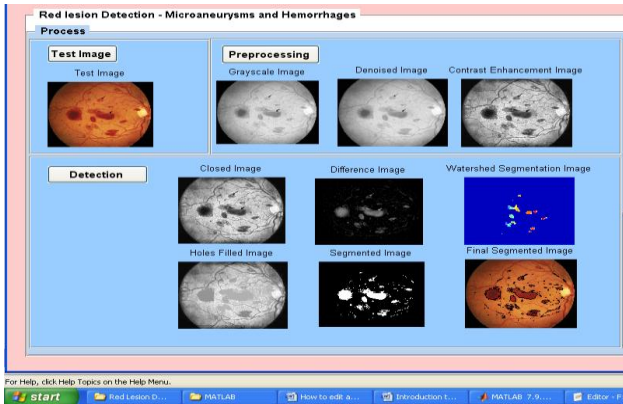


Fig. 2 Image Segmentation step

Step-III Feature Extraction

Our major contribution is a new set of shape features that do not require precise segmentation of the candidates. We consider every regional minimum as a candidate. Since the boundaries of the minima do not necessarily correspond to the edges of the structures of interest, we propose to extract shape features through the process of morphological image flooding. The DSF together with color features are extracted for each candidate. The difference with a vessel segment is that the layers evolve more anisotropic ally in the latter case, following the vessel's orientation, and, at some intensity threshold, start merging with other vessel segments. This novel set of features, called Dynamic Shape Features (DSF). A shape can be described by different aspects. The shape parameters are gravity, Inertia, variance, energy, Eccentricity, Circularity ratio, Rectangularity, Solidity, Euler number, Profiles, Hole area ratio, Convexity, Area, Perimeter, Length. DSF calculation which is done based on the inbuilt MATLAB function.

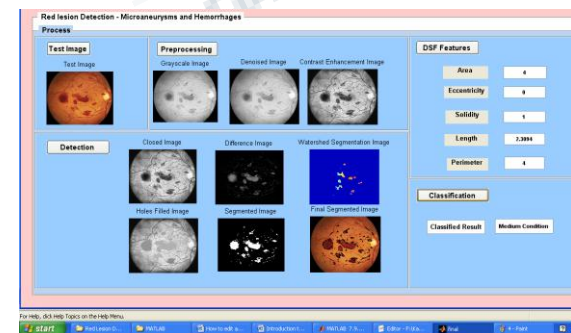


Fig.3 Feature Extraction Step

Step-IV Classifying result

Classifies individual pixel based on this spectral information. The classification is done over segmented image using Random Forest (RF) Classifier. One of the foremost common ways or frameworks utilized by knowledge scientists at the rose knowledge science skilled follow clusters is Random Forests.

The Random Forests formula is the simplest among classification algorithms able to classify giant amounts of information with accuracy. Random Forests are associate degree ensemble learning technique (also thought of as a kind of nearest neighbor predictor) for classification associate degree regression that construct variety of call trees at coaching time and outputting the category that's the mode of the categories output by individual trees.

Figure 4 shows classification result of proposed and existing work. The affected lesion will outputted as severe, medium or low condition during classification part.

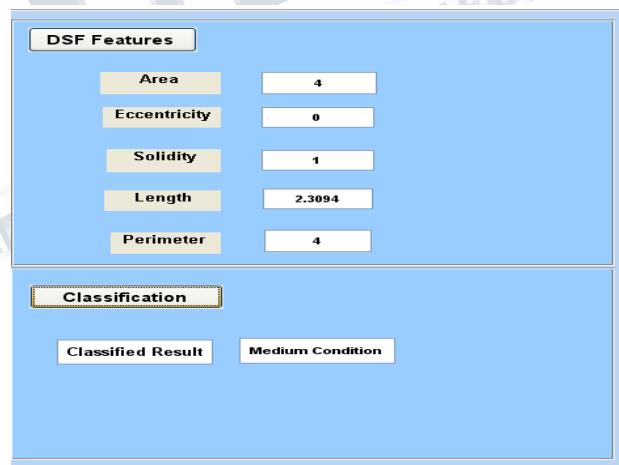
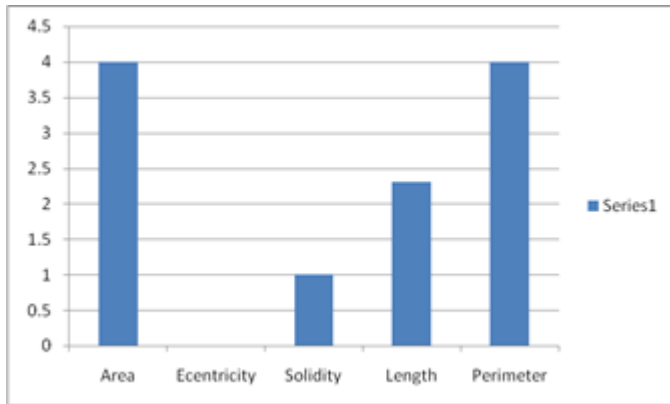


Fig.4 Classifying Result

IV. RESULTS

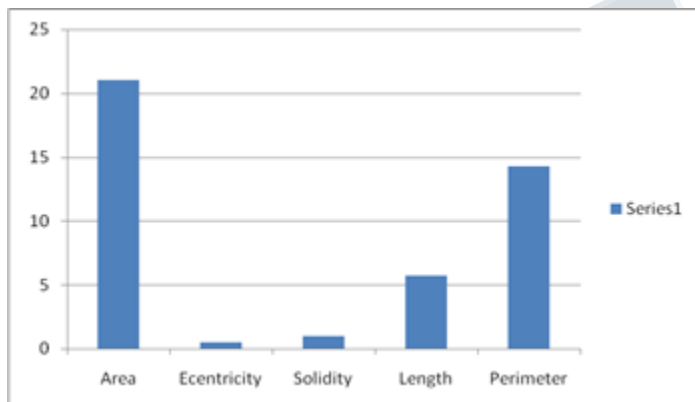
The overall experimental setup is done with the help of MATLAB software. The DSF parameters are withdrawn in the final step .As the values decide the result of diabetic retinopathy. The following graph shows the result evaluation considering two sets of images as deciding the conditions of diabetic retinopathy.

1. Medium Condition



Graph 1. Result of Medium Condition

2. Severe Condition



Graph 2. Result of severe condition

V. CONCLUSIONS

The Red lesion in retina is being recognized by using computer aided software MATLAB and it is being classified based on the amount of red lesions that is present in the retina. A novel red lesion recognition method based on a new set of shape features, the DSFs, was presented and evaluated. The results demonstrate the strong performance of the proposed method in detecting both MAs and HEs in fundus images of different resolution and quality and from different acquisition systems.

The method outperforms many state-of-the-art approaches at both per-lesion and per-image levels. Dynamic Shape

Features have proven to be robust features, highly capable of discriminating between lesions and vessel segments. The concept of DSFs could be exploited in other applications, particularly when the objects to be detected do not show clear boundaries and are difficult to segment precisely.

Further work focusing on bright lesion and neo vessel recognized will complete the proposed system and allow automatic DR grading. Thus the result is being classified based on the random forest classifier.

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