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Diabetic Retinopathy using Image Processing Detection, Classification and Analysis

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Abstract

Diabetic retinopathy is one of the complicated and crucial diagnosis step in diabetes. That develops in most of the patients with longstanding illness, and the leading cause of blindness in the developed countries. Effective treatments for diabetes are available, though it requires early diagnosis and the continuous monitoring of diabetic patients. Manual grading of these images is slow and resource demanding to determine the severity . In this work we are not only focusing on the early detection of DR but also continuous monitoring of DR using digital image processing. The presence of micro aneurysms (MAs) on the Retina is the first and most characteristic symptom of this disease. The recognition of MAs is an essential step in the diagnosis. In proposed method Diagnosis of DR is performed by the evaluation of retinal (fundus) images.

Keywords

Biomedical image processing, image classification, pattern recognition.

1. Introduction

In recent decades with enriched life style it has been observed increase cases of diseases like diabetes. According to recent survey, 4% of the country population has been diagnosed of diabetes alone and it have been recognize and accepted as one of the main cause of blindness in the country if not properly treated and managed .Early detection of diabetes have identified as one of the way to achieve a reduction in the percentage of visual impairment caused by diabetes with more emphasis on routine medical check with the use of special facilities for detection and monitoring of the said disease. A lot of approaches have been suggested and identified as means of reducing stress caused by this constant checkup and screening related activities among which is the medical digital image signal processing for diagnosis of diabetes related disease like diabetic retinopathy using image of the retina. Diabetic Retinopathy (DR) is an eye disease diabetic retinopathy that can lead to partial or even complete loss of visual capacity, if left undiagnosed at the initial stage.

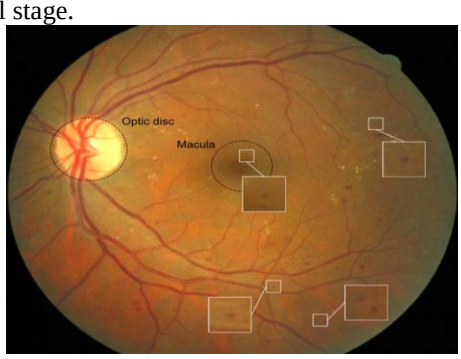

Fig 1: An example of fundus image showing signs of DR

Micro aneurysms are earliest signs of diabetic retinopathy vessels and abnormal features like exudates they arise due to high sugar levels in the blood .there will be 79 million people with diabetes by 2030, making the India comprehensive analysis and grading of Diabetic capital of the world. Micro aneurysms are first clinically diagnosed with diabetes. Chances of observable lesions indicating diabetic retinopathy are 17% during the first 5 years. And increases to 97% after 15 years of diabetic retinopathy screening system. This increases more work have been done to improve some of the existing screening methods.

A. Background and relevance

Morphological approach is the first computerized approach for the segmentation of retinal MAs. Which calculate the maximum of morphological openings There are linear structuring elements of different orientations. This step results in an image from which the structures that are smaller than the structuring element are missing. [1].

A limitation of the morphological approach is that the usage of too large structuring elements would result in the detection of tight vessel carvings' as possible MAs .If the length of the linear structuring element is chosen so that no parts of the vasculature will be wrongly detected, true MAs will be lost, since no circular structure that is larger than the structuring element can be detected in this way.[1] Non

morphology based methods have also been investigated using Gaussian masks of different size and standard deviation, and calculated the maximal pixel wise correlation with the original image .[2]
The drawbacks associated with above two methods are overcome with proposed method.

2. Proposed method

The method we propose here realizes the detection of MAs through the analysis of the intensity values along discrete line segments of different directions centered at the candidate pixel. The detection method considers an entirely different approach by dividing the detection process into the steps of candidate extraction, feature extraction, classification, and score determination. The results of the detection process in the same online competition proved that it is not just able to remarkably outperform its predecessor, but it turned out to be the best no ensemble based MA detector among all participants.[2] Input image is the inverted green channel of a fundus image, since this way MAs, hemorrhages, and the vasculature will appear as bright structures, i.e., local intensity maximum regions. By considering the binary region of interest (ROI) mask we get required input image.Having spatial resolution of the diameter is equal to 540 pixels, since this was the smallest ROI diameter we came across in the publicly available fundus image sets. It is possible to apply ROI on images of different size.[3] For better understanding of proposed method its schematic workflow is shown in Fig.2.

B. Image Processing

Preprocessing of any image gives smoothening before actual detection step. Because many fundus images are available in a lossy compressed format .This compression resulting in the distortion of small structures such as MAs. Since the method particularly relies on the local intensity distribution of MA, it is important to reduce the effect of noise. By applying convolution with a Gaussian mask with a variance of 1.0. Our experiments showed that this amount of smoothing suppressed noise sufficiently while preserving true MAs.

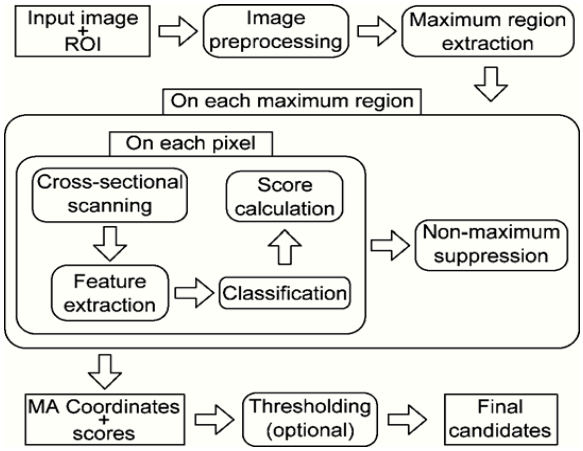

Fig 2: Schematic workflow of proposed method

C. Local Maximum Region Extraction

By applying Gaussian mask on image resulting in intensity distribution. MAs are local intensity maximum structures on the preprocessed retinal image. Which means that every MA region contains at least one regional maximum. A local maximum region (LMR), of a gray scale (intensity) image is a connected component of pixels with a given constant intensity value. Every neighboring pixel of the region has strictly lower intensity [4]. Therefore, it is sufficient to consider only the LMRs of the preprocessed image as possible MA candidate regions. We applied a simple breadth-first search algorithm, similar to the one described in[5] for the calculation of gray scale morphological reconstruction. In this algorithm pixels of the image are processed sequentially, and compared to their 8-neighbors. If all other neighbors of pixel have lower intensity, then the pixel itself is a LMR. If there is a neighboring pixel with higher intensity, then the current pixel may not be a maximum. A pixel is considered to be a possible maximum if all neighboring pixels have lower or the same intensity, in which case pixels with the same intensity are stored in a queue, and tested in the same way.

D. Peak Detection

Peak detection is performed to obtain cross-section profiles. These cross-section profiles decide whether a peak is present at the center of the profiles, i.e., at the location of the candidate point for a specific direction. We calculate several properties of the peak, and the final feature set consists of a set of statistical measures that show how these values vary as the orientation of the cross-section is changing. In this way, the variation of important characteristics, such as symmetry and shape of the structure, and its

difference from the background can be numerically expressed.

E. Feature Set

Let μT, σT, and cvT denote the respective mean, standard deviation and coefficient of variation of the values in set T ,where the coefficient of variation is the ratio of the standard deviation and the mean,

$Cv = \sigma/\mu$

Let us consider the following feature set for classification [fig.3].

F={μPWIDTH, σPWIDTH ,μTWIDTH, σTWIDTH, σRSLOPES, *cv*RHEIGHT, *cv*PHEIGHT}

Where,

μPWIDTH= extension of candidate object

σPWIDTH = symmetry of extension

μTWIDTH, σTWIDTH=inner region of candidate

σRSLOPES =higher value for vessel crossing

***cv*RHEIGHT, *cv*PHEIGHT = variation in sharpness**

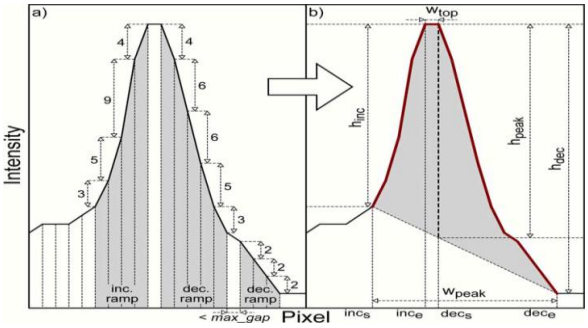

Fig 3: Increasing and decreasing ramps on a sample profile of the peak detection

Using this feature we are able to distinguish MAs from most common interfering objects, such as small disconnected vessel fragments, vessel crossings and bifurcations, retinal hemorrhages that are only slightly larger than MAs, or local darkening on the vessels.

F. Classification

For classification, we used a naïve Bayes (NB)[6]classifier. Which is simple and robust probabilistic algorithm that assumes the individual features to be independent. The training set obtained from cross-section profiles consists of both positive and negative MA examples. Usually, it is rather straightforward to obtain the feature vectors of positive instances of the training set, since in most public datasets the coordinates of MAs on the images are given. The non-MA set consists of false positives. The training of a NB classifier means the estimation of the class priors and feature probability distributions. Following the common practice when dealing with continuous data, we assume that the feature values in each class are of Gaussian distribution. This also means that the parameters of the distribution can be estimated using the sample means and variances of the training data for the given feature. Experiments showed that there was only a minimal difference in the final performance, but NB gave a slightly better result. Besides, its low computational time and its robustness are also advantageous.

G. MA Score Calculation

The MA score is calculated using the formula:-

$$SCORE = \frac{\min PHEIGHT \times \mu RSLOPES}{1 + \sigma PWIDTH + \sigma TWIDTH + \sigma RSLOPES + \sigma RHEIGHT + \sigma PHEIGHT}$$

The score calculated this way will be maximal, when the variables in the denominator equal zero, and it assigns higher score to locally more distinctive candidates with sharper edges, while taking into consideration that variation in the important features should be as low as possible. We note that instead of the coefficient of variation of RHEIGHTS and PHEIGHTS the standard deviations are considered.

The final step of the proposed method is the non-maximum suppression. All points of the region are considered as candidate pixels. Non-maximum suppression at this point refers to the operation of selecting the point with the highest score from every maximum region that will represent the corresponding candidate. Therefore, points with non-maximal score in a candidate region are neglected, and the output is a set of coordinates and the corresponding score values. We note that the MA scores are not normalized values. Optionally, it is possible to have a binary output for the MA candidates with an appropriate Thresholding of the score values.

3. Case study

A. Performance Evaluation

The most wide spread technique for the performance evaluation of abnormality detection methods in medical images is the usage of free response ROC curves. It plots sensitivity against the average number of false positives per image [6].

B. Retinopathy Online Challenge

The Retinopathy Online Challenge is an international online competition dedicated to compare the accuracy of micro aneurysm detectors under the same conditions. This gives each participating team the opportunity to train their methods on the training set, and submit their results obtained on the test set, in the form of pairs of candidate coordinates and confidence values. The final score of a method is calculated as the average sensitivity at seven false positive rates (1/8, 1/4, 1/2,1, 2,4, and 8 false positives per image).

Assembling the positive (MA) set is rather straightforward. However compilation of the negative (non-MA) set is more complicated, Since its elements have to be selected manually. To construct the training feature set for the classifier of the proposed method. We took the official marking of the MAs on the training set as a basis, and we sorted out the ambiguous ones manually. In the case of the ROC the proposed method achieved higher sensitivity at every false positive rate, proving its robustness in a scenario; where there is no possibility to repeatedly retain the method on every new image set.

4. Conclusion

The method proposed in this paper give more speed for processing of each image. This increase in speed is due to the lower number of candidate pixel, the fast feature extraction and classification. The number of pixels to be processed is significantly reduced by considering the local maxima of the preprocessed image. We use the classifier setup obtained on the ROC training set, which proves the robustness of the proposed method. The fact that the performance difference between the currently proposed and previous method is its tolerance against noise corruption from different image sources. By adding optic disk detection step it is possible to distinguish the MA candidates. This cross section analysis based method can be used for other medical related image processing. It involves recognition of circular or slightly elongated structures of image. It is able to distinguish vessel bifurcations and crossings.

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