



Retinal Microaneurysm Exclusion on Optic Disc and Detection Using Cross Section Profile Analysis

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ABSTRACT: Diabetic retinopathy (DR) is one of the complications of diabetes that develops in most of the patients with long- standing illness and the leading cause of blindness in the developed countries. Though effective treatments for DR are available it requires early diagnosis and the continuous monitoring of diabetic patients. Diagnosis of DR is performed by the evaluation of retinal (fundus) images. Manual grading of these images to determine the severity of DR is rather slow and resource demanding. The presence of microaneurysms (MA's) on the retina is the first and most characteristic symptom of this disease .MA's on the retina appear as small, round shaped, red dots. No additional vessel or optic disc detection step is applied in existing system. The proposed method proved to be able to distinguish vessel bifurcations and crossings from MA's rather well however, some of the false positives come from the region of the optic disc. Since the contrast is very high in the region of optic disc, sometimes a rather high score is assigned. Though the existing method showed convincing performance, this could probably be further improved by adding an optic disc detection step and excluding MA detections within this region. The proposed method realizes MA detection through the analysis of directional cross-section profile centered on the local maximum pixels of the pre-processed image. Peak detection is applied on each profile and a set of attributes regarding the size, height, and shape of the peak are calculated subsequently. The statistical measures of these attribute values as the orientation of the cross-section changes constitute the feature set that is used in a naive bayes classification to exclude spurious candidates. A formula is given for the final score of the remaining candidates, which can be threshold further for a binary output. The proposed method has been tested in the retinopathy online challenge, where it proved to be competitive with the state-of-the-art method.

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the complications of diabetes. Diagnosis of Diabetic Retinopathy is performed by the evaluation of retinal images. The presence of microaneurysms on the retina is the first and most characteristic symptom of this disease. DR is a severe and widespread eye disease which can be regarded as a manifestation of diabetes on the retina. It is a major public health problem and it remains the leading cause of blindness in people of working age (20-65 years). After duration of 10years, around 7% of people with diabetes will have diabetic retinopathy, rising to 90% after 25 years. DR is a leading cause of blindness both in United States and Asia.

Diabetic retinopathy occurs when the increased glucose level in the blood damages the capillaries. It is characterised and graded by the development of retinal microaneurysms(MA's), haemorrhages and exudates. MA are focal dilations of retinal capillaries and appear as small, round, dark red dots. MA's are swelling of the capillaries caused by a weakening of the vessel wall. In retinal photographs, although the capillaries are not visible, MA's appear as dark red isolated dots that are by definition less than the diameter of the major optic vessel.

Effective treatment for DR is available, though it requires early diagnosis and the continuous monitoring of diabetic patients. Diagnosis of DR is performed by the evaluation of retinal images. Manual grading of these images to determine the severity of DR is rather slow and resource demanding. Therefore for early diagnosis of DR there is a need for automatic detection of microaneurysms in retinal images



IMAGE PREPROCESSING

The proposed method particularly relies on the local intensity distribution of MAs, it is important to reduce the effect of noise. This amount of smoothing suppressed noise sufficiently while preserving true MAs.

LOCAL MAXIMUM REGION EXTRACTION

A simple breadth-first search algorithm is applied for the calculation of grayscale morphological reconstruction. Pixels of the image are processed sequentially, and compared to their 8-neighbors. If all neighbours have a lower intensity, then the pixel itself is a LMR. If there is a neighbouring pixel with higher intensity, then the current pixel may not be a maximum.

Pixels of a LMR are considered individually as possible candidates, and the pixel with the maximum final score will represent the region; this procedure is referred to as non maximum suppression.

CROSS-SECTIONAL SCANNING

To examine the surrounding of a single maximum pixel in a MA candidate region, the intensity values along discrete line segments of different orientations, whose central pixel is the candidate pixel, are recorded. In this way, a set of cross-sectional intensity profiles is obtained.

PEAK DETECTION AND PROPERTY MEASUREMENT ON THE CROSS-SECTION PROFILES

On the obtained cross-section profiles a peak detection Step is performed. Our aim is to decide whether a peak is present at the center of the profile, i.e., at the location of the candidate point for a specific direction. Several properties of the peak are calculated, 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. This way, the variation of important characteristics, such as symmetry and shape of the structure, and its difference from the background may be numerically expressed.

The basis of the peak detection method applied is to locate strictly monotonic segments (ramps) of the profile. Let P denote a profile and $P[i]$ its i th value. A ramp is defined as a segment of the profile, i.e., $P[m], P[m+1], \dots, P[n]$ where the sign of the difference between the consecutive values is nonzero, and the same along the segment, i.e., $\text{sgn}(P[i]-P[i-1])=\text{sgn}(P[i+1]-P[i])$ for every $m < i < n$. Additionally, the absolute difference between consecutive values should not be less than parameter min diff, and the height of the ramp, i.e., the absolute difference between the first and last value should be not less than parameter min height, either. The value of min diff acts as a lower threshold for the slope of the ramps, and it control show sharp the intensity transition should be. The purpose of the min height parameter is to give a lower noise threshold. Based on whether $\text{sgn}(P[i+1]-P[i])$ is positive or negative, the ramps are considered to be increasing or decreasing ramps, respectively. The cross-section profiles of several MAs are examined, and found that by setting min diff to 2, and the min height to 3, small monotonic segments that are clearly noise artifacts can be eliminated.

FEATURE SET AND CLASSIFICATION

After the cross-sectional scanning and peak detection steps are performed for every scan direction on a given candidate, several statistical measures of the resulting directional peak properties are calculated. The increasing-and decreasing ramp height values are stored in the RHEIGHTS set, likewise, the ramp slope values are stored in RSLOPES. The TWIDTHS, PWIDTHS, and PHEIGHTS sets contain the top width, peak width, and peak height values, respectively. Let μ , σ , and CV 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, i.e., $CV = \sigma/\mu$. The following feature set for classification is considered.

$F = \{\mu \text{ PWIDTHS}, \sigma \text{ PWIDTHS}, \mu \text{ TWIDTHS}, \sigma \text{ TWIDTHS}, \sigma \text{ RSLOPES}, cv \text{ RHEIGHTS}, cv \text{ PHEIGHTS}\}$

For classification, a naïve Bayes (NB) classifier is used, a simple and robust probabilistic algorithm that assumes the



individual features to be independent. The training set 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 the previously described most common false positives. The training of a NB classifier means the estimation of the class priors and feature probability distributions.

II. RELATED WORKS

Atsushi Mizutani^a, Chisako Muramatsua, Yuji Hatanakab, Shinsuke Suemoria, Takeshi Haraa, Hiroshi Fujita[17] have investigated a computerized method for the detection of microaneurysms on retinal fundus images, which were obtained from the Retinopathy Online Challenge (ROC) database. The ROC provides 50 training cases, in which “gold standard” locations of microaneurysms are provided, and 50 test cases without the gold standard locations. In this study, the computerized scheme was developed by using the training cases. Although the results for the test cases are also included, they mainly discuss the results for the training cases because the “gold standard” for the test cases is not known. After image pre-processing, candidate regions for microaneurysms were detected using a double-ring filter. Any potential false positives located in the regions corresponding to blood vessels were removed by automatic extraction of blood vessels from the images. Twelve image features were determined, and the candidate lesions were classified into microaneurysms or false positives using the rule-based method and an artificial neural network. The true positive fraction of the proposed method was 0.45 at 27 false positives per image. Forty-two percent of microaneurysms in the 50 training cases were considered invisible by the consensus of two co-investigators. When the method was evaluated for visible microaneurysms, the sensitivity for detecting microaneurysms was 65% at 27 false positives per image. Our computerized detection scheme could be improved for helping ophthalmologists in the early diagnosis of diabetic retinopathy.

L. Gagnon, M. Lalonde, M. Beaulieu, M.-C. Boucher [26] present an overview of the design and test results of a practical image processing procedure to detect all important anatomical structures in color retinal images. These structures are the Optic Disk (OD), the macula (fovea) and the retinal network. Detection of anatomical structures is important in many ways: · Segmenting the OD is a key pre-processing element in many algorithms designed for automatic extraction of anatomical structures and detection of retinal lesions. This is notably the case for vessel tree extraction, for which large vessels located in the vicinity of the OD can serve as seeds for vessel tracking procedures. Masking the OD also helps reducing bias regarding retinopathy-related lesions detection. · Macula encircling helps establishing statistics regarding lesions position for disease gradation. The relatively constant distance between the OD and the macula center can be used as *a priori* knowledge to help positioning the macula. · Vessel tracking provides a map of the retinal vessels of the eye, from which a reference frame may be derived that can ease the process of positioning other fundus objects and lesions with respect to a natural “coordinates systems”. Vascular network also allows the localization of stable anchor points (such as bifurcation) needed for image registration as well as the characterization of veins associated to specific pathology like venous beading (veins tortuosity that reflects the progress of diabetic retinopathy). Finally, vessel detection turns out to be helpful to other recognition algorithms that requests the removal of the vascular network.

Joes Staal, Michael D. Abràmoff Meindert Niemeijer, Max A. Viergever and Bram van Ginneken[21] explained that characteristics of vessels plays an important role in a variety of medical diagnoses. For these tasks measurements are needed of e.g., vessel width, color, reflectivity, tortuosity, abnormal branching, or the occurrence of vessels of a certain width. When the number of vessels in an image is large, or when a large number of images is acquired, manual delineation of the vessels becomes tedious or even impossible. The focus of this paper is on the automated segmentation of vessels in color images of the retina. These images, also known as fundus images, are acquired by making photographs of the back of the eye. We are interested in vessel segmentation for screening of diabetic retinopathy. Diabetes is a disease that affects about 5.5% of the population worldwide, a number that can be expected to increase significantly in the coming years. About 10% of all diabetic patients have diabetic retinopathy, which is the primary cause of blindness in the Western World. Since this type of blindness can be prevented with treatment at an early stage, the WHO advises yearly ocular screening of patients. Automation will facilitate this screening. Knowledge about the location of the vessels can aid in screening of diabetic retinopathy, e.g., to reduce the



number of false positives in the detection of microaneurysms to serve as a means for registration of images taken at different time instants or at different locations of the retina, or to find the location of the optic disc and the fovea. Previous methods for vessel segmentation in images of the retina can be divided into two groups. The first group consists of rule-based methods and comprises vessel tracking, matched filter responses, grouping of edge pixels, model based locally adaptive threshold, topology adaptive morphology-based techniques. The second group consists of supervised methods, which require manually labelled images for training. To the best of our knowledge, the only published method in this category is the neural network scheme for pixel classification by Sinthanayothin *et al.* Our method belongs to the last category. In our opinion, a pixel representation is not optimal for vessel structure. Therefore, our approach is based on the intrinsic property that vessels are elongated structures. This observation leads to a primitive-based method, which we refer to as PBM. Our algorithm uses image primitives formed from image ridges that are grouped into sets that approximate straight line elements. The sets are used for two purposes. First, features are computed which together with a classifier give a probability that the line element is part of a vessel. Second, the sets divide the image into patches by assigning every pixel of the image to its nearest primitive. Within each patch, the line element defines a local coordinate frame in which local features can be extracted for every pixel. The probability that the line element is part of a vessel is one of these features. The features are used to classify the pixels in the patch into vessel and non vessel. Many of the published methods have not been evaluated on large datasets or fail to give good results for large numbers of images as encountered in a screening process. In an evaluation is done on vessel segments and bifurcations. Only is an evaluation on complete manually labelled images presented. We have constructed a database of manually labelled images for training and evaluation of our method. The database consists of 40 images taken from a screening programme for diabetic retinopathy in the Netherlands. We compare our method with two rule-based methods. The first one is the method of Hoover *et al.* the second one the method of Jiang *et al.* Hoover *et al.* have collected a database of manually labelled images, which is publicly available together with the results of their method. For comparison, our system is evaluated on their database too.

Clara I. Sánchez, Roberto Hornero, Agustín Mayo, María García[19] proposed that Retinal images are widely used by ophthalmologists and primary care physicians for the screening of epidemic eye diseases, such as Diabetic Retinopathy (DR). DR is one of the leading causes of blindness and vision defects in developed countries. Due to its prevalence and clinical significance the research community has attempted to improve its diagnosis and treatment by developing algorithms to perform retinal image analysis. Retinal images permit a high quality permanent record of eye fundus for detecting early signs of DR and monitoring its progression. Moreover, their digital nature allows automatic analysis to reduce the workloads of the ophthalmologists and the health costs in the screening of the disease. Early detection and diagnosis of DR is crucial for the prevention of visual loss. Among the early signs of DR, Microaneurysms (MAs) are the first signs of the presence of DR1. Therefore, their detection is of paramount importance for the early diagnoses of DR. MAs are a small dilation of retinal capillaries due to the weakness of the vessel walls. On the retinal surface, they appear as small round dark red dots with about 10 to 100 μm in diameter. Several techniques have been developed for MA detection in fluorescein angiographies and in color fundus images based on a variety of techniques. MAs have been detected using template matching² and mathematical morphology. However, supervised methods, such as statistical classifiers⁴⁻⁶ and k-nearest neighbour classifier have been also applied. Because the brightness, contrast and color of MAs vary a lot among different patients and, therefore, different images, these methods would not work in all the images used in clinical environment. In this work we propose a robust statistical approach based on mixture model-based clustering followed by a classification step using logistic regression. The innovative segmentation approach based on a statistical mixture model based clustering allows a robust separation of the foreground and background scenes and, specifically, a segmentation of MAS in a totally unsupervised manner. The method is robust to the changes in the appearance of retinal fundus images typically encountered in clinical environments, achieving a satisfactory MA detection performance.

III. PROPOSED SYSTEM

Optic disc (OD) detection is a main step while developing automated screening systems for diabetic retinopathy. In this paper a method to automatically detect the position of the OD in digital retinal fundus images is proposed. The method starts by normalizing luminosity and contrast through out the image using illumination



equalization and adaptive histogram equalization methods respectively. The OD detection algorithm is based on matching the expected directional pattern of the retinal blood vessels. Hence, a simple matched filter is proposed to roughly match the direction of the vessels at the OD vicinity. The retinal vessels are segmented using a simple and standard 2-D Gaussian matched filter. Consequently, a vessels direction map of the segmented retinal vessels is obtained using the same segmentation algorithm. The segmented vessels are then thinned, and filtered using local intensity, to represent finally the OD-center candidates. The difference between the proposed matched filter sized into four different sizes, and the vessels' directions at the surrounding area of each of the OD-center candidates is measured. The minimum difference provides an estimate of the OD-center coordinates. The proposed method was evaluated using a subset of the STARE project's dataset, containing 81 fundus images of both normal and diseased retinas, and initially used by literature OD detection methods. The OD-center was detected correctly in 80 out of the 81 images (98.77%). In addition, the OD-center was detected correctly in all of the 40 images (100%) using the publicly available DRIVE dataset.

IV. CONCLUSION

A method for the detection of MAs on retinal images, based on the principle of analyzing directional cross-section profiles centered on the candidate pixels of the pre-processed image. The number of pixels to be processed is significantly reduced by only considering the local maxima of the pre-processed image. Peak detection is applied on each profile, and calculate a set of values that describe the size, height, and shape of the central peak. The statistical measures of these values as the orientation of the cross-section changes constitute the feature set used in a classification step to eliminate false candidates. A formula is derived to calculate the final score of the remaining candidates based on the obtained feature values.

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