

Manual Microaneurysm Detection Support with Size- and Shape-based Detection

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Abstract—The goal of this paper is to detect visible microaneurysms in retina using size and shape.

To achieve the desired goal multi-stage image processing techniques are used. The vascular network and the red regions are highlighted using morphological methods, so these can be segmented with region growing algorithms. Mask is generated that contains only the blood vessels. The red blobs of original images are classified using the generated binary image and their produced skeleton.

Our goal is to detect as many as possible microaneurysms taking their shape and size into account. Experiments with manual settings on the test images showed approx. 50% of detection performance, and it can be further improved by development of pre-processing and increasing classification criteria.

The developed system can help the manual evaluation of microaneurysms, hence can accelerate of the work of doctors.

Index Terms—medical image processing, microaneurysm detection, image segmentation, skeletonization

I. INTRODUCTION

Diabetes is one of the most widespread diseases in the world. One possible complication of the disease is diabetic retinopathy, which is a disease of the eye, and is a leading cause of adult blindness. The first significant symptoms of diabetic retinopathy are the microaneurysms. In the early stages observation of microaneurysms can be crucial, because at that time the disease can be treated. The manual microaneurysm detection is a lengthy task for professionals, and it requires a number of resources. Our goal is the detection of visible microaneurysms by size and shape.

A. Diabetic retinopathy

Walls of blood vessels providing blood supply to the retina gradually weakens due to diabetes, thereby can be swelled and blocked. The human body try to remedy it by formation of new blood vessels. However, the disordered and weak small blood vessels are not able to maintain the right blood supply, they can be burst, thereby exudate and blood can leak out to the vitreous body. The blood flown to vitreous body obstructs the path of light to the retina, thereby worsens vision. If the fluid flows below the retina, so it can move from back wall of the eye, such distorts vision. In serious cases the retina may detach, which causes blindness.

TABLE I

CATEGORIES OF DIABETIC RETINOPATHY (DR). MA AND V ARE THE NUMBERS OF MICROANEURYSMS AND HEMORRHAGES, RESPECTIVELY. [1]

DR stadium	MA value	V value
0. category: nothing	$MA = 0$	$V = 0$
1. category: mild	$1 \leq MA \leq 5$	$V = 0$
2. category: moderate	$5 < MA < 15$	$0 < V \leq 5$
3. category: serious	$MA \geq 15$	$V > 5$

B. Microaneurysms

The circle shaped swelled vessels are called microaneurysms [1], which can be detected in early stages of the disease. Based on consensus the maximal diameter is equal to cross-section of the largest vessel. Their number correlates seriousness and probable progression of the disease. This relationship is represented in a categorized view in Table I.

Microaneurysms are noticeable in fundus images of retina, further damage can be prevented with in-time started therapies.

C. Theoretical steps of our solution

The inputs of our process are digital funduscamera images (see Figure 1). These are traditional color images taken by micro-camera [2]. There is also another type of capturing (ie. fluorescence angiography), but the preparation procedure is unpleasant for the patient, so we are also orientated towards the first type of images.

During producing the prototype of pre-processing [3] the information content of different color channels were examined. After locally contrast improvement, the details became sharper. The illumination problem was solved by application of median filter, and background estimation, using subtraction operation. Since the intensity values became too low, a further contrast enhancement was applied on the image.

Using region growing algorithm [4], [5] and connected component analysis the network of blood vessels was produced, as well as the image containing the possible microaneurysms. The largest cross-section as maximal microaneurysm size was searched with a special algorithm in the largest component. Then compared to this determined size the regions considered as possible microaneurysms were examined based on size and shape.

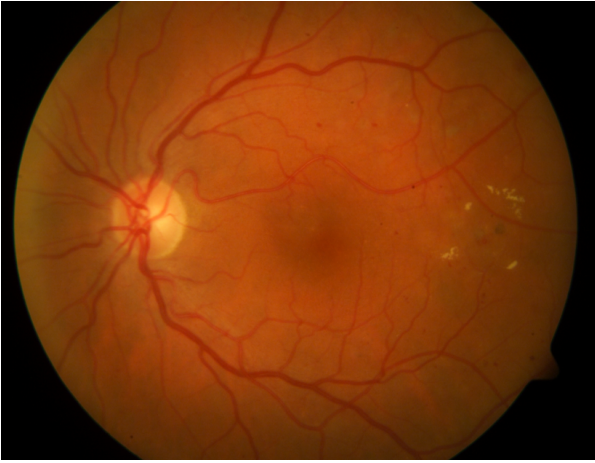


Fig. 1. Digital funduscamera image

II. SIMILAR SYSTEMS AND APPROACHES

Before explaining details of our solution, a summary is given of similar systems. These systems are the bases of our further research and conclusions.

Walter et al. [6] used an improved gray-scale image contrast enhancement process, which emphasizes the details. The mentioned algorithm performs morphological closing of the image. The method detects small, dark objects determined by the applied structuring element. In final step it performs a thresholding, and the remaining objects are noted as microaneurysms.

The closing process was thought to be very useful as well as in our projects. During pre-processing the objects became more organized and separated, hence the further algorithms also became more efficient. Incomplete, broken blood vessels became more homogeneous after the segmentation. The disadvantage of closing is that two neighbour microaneurysms can merge one larger object, so they can not be detected as separate objects. Sometimes noises are also merged, and during the further process it will be detected incorrectly as a microaneurysm.

In an other approach [7] median filtering was performed in the green channel of the image for the purpose of noise reduction. This method is widely used, for example in [8], and this process determines illumination of the background. It subtracts the image of green channel from the modified image, thereby forming an improved hue image [9].

It performs a morphological top-hat transform with twelve, 15° rotated structuring element. The maximum of the transformations is subtracted from the image, thus the largest components of the image are removed. Gauss filtering is the next step, and after that comes a binarization with predefined thresholds, then the original sizes are reconstructed using a region growing step. The result is such an image, which consists only the candidates.

Since at most projects it was used, we also started from the green channel of original images. In this channel was the drawing of either blood vessels or microaneurysms the most

separated based on our experiments. The difference of median filtering with big kernel size was also used in our project, this largely removed the background of the captures. Since our region growing binarization algorithm handle more easily higher contrast images, it was necessary to use a contrast stretching after subtraction. However, many details were still missing from the image, so before subtraction another adaptive contrast enhancement was used locally in the image. This approach improved the detection of smaller objects.

In [10] the described method firstly performs a Gaussian filtering in the green channel of the image, then makes an inversion as pre-processing steps. It analyses intensity profiles for each pixel from several directions between -90° and $+90^\circ$ along equidistant lines. The checked pixels are organized to blocks. On each profile the maximal intensity value and the intensity value of actual pixel is used for an adaptive thresholding. They are reconstructed into two-dimensional coordinates, and then the algorithm performs averaging and hysteresis thresholding, hence the candidates are generated.

The method works based on the followings, the intensity profiles of blood vessels and microaneurysms analysed from all directions are different because of their shape. In case of microaneurysm outlier value can be observed in each direction of intensity profiles. This is missing in case of blood vessel. Our purpose was to separate objects from each others using the mentioned method, and to find the cross-section of the largest blood vessel, as well as detect microaneurysms as circle shaped blobs. During testing this algorithm had to be expanded such that to produce skeleton images, because the program ran very slowly. So this algorithm could be used starting from largely the center of objects. The running time decreased, since the number of unnecessarily checked pixels became less.

Another algorithm [11] converts the RGB components into the IHS model, which consists the intensity, hue and saturation. Then it carries out a local adaptive contrast enhancement, and after that the image is re-transformed into the RGB color space. Before the microaneurysm detection the parts of eye is recognized, so the number of candidates can be reduced. The fovea, the blind spot, and the blood vessel network are removed from the image by correlation check, the analysis of difference of neighbouring pixels, and usage of multi-layered perceptron neural network, respectively. To detect microaneurysms and hemorrhages green channel was used, because the red color has higher contrast here. The edges are enhanced better with so-called 'Moat operator'. Objects are detected by using of recursive region growing algorithm and thresholding, which are divided into to parts: the group of microaneurysms and hemorrhages, and all other objects. Because the network of blood vessels was detected before, the pixels of vessels are not assigned to any groups. This method was applied in [12] too.

We met later this project in our research. The proposed region growing algorithm is also used in our project, but we make segmentation of blood vessels and microaneurysms with that. In the pre-processing phase we do not use other color spaces, but in the green channel use local adaptive thresholding

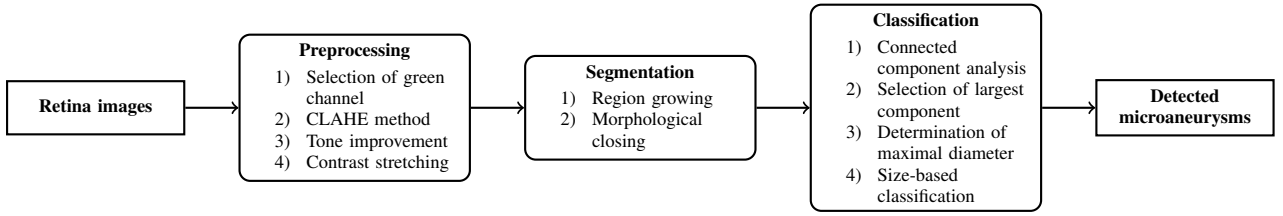


Fig. 2. The structure of the developed algorithm.

as well to separate better blood vessels and microaneurysms from the background.

III. IMPLEMENTATION OF OUR PROJECT

The developed algorithm consists three steps. The first is the pre-processing, then comes the segmentation and at the end the classification phase. In Figure 2. the steps are shown in a flow chart diagram.

A. Pre-processing

Firstly the RGB channels of images were analysed (see Figure 3.). That was found, the most appropriate channel is the green one. On this channel the blood vessels and microaneurysms are the most prominent. One example of comparison can be seen in Figure 3. This selection is very useful, because selecting only one channel we can deal with only a one-channel image, which is similar to intensity ones.

At next step the contrast limited adaptive histogram equalization (CLAHE) [13] was used. This transformation highlights locally the blood vessels from the background, thus supporting further processing.

In the prepared image a tone improvement was performed using a median filtering with 64×64 size kernel. The eq. 1 shows the transformation, where f is the input image, f_{med} is the image after median filtering, and g is the result.

$$g = f_{med} - f \quad (1)$$

The difference image excludes the most part of image background.

To separate the remained background pixels from the searched object, a contrast enhancement was applied. Thus, on the result image blood vessels are more significant, and because the intensity value of microaneurysms are similar to the intensity of vessels, the microaneurysms are also more enhanced. An example of the result image can be seen in Figure 4.

B. Segmentation of blood vessels and microaneurysm

Several binarization possibilities have been examined. First, the simple threshold-based binarization, where the threshold determination was the main problem. At the choice of several values two problem generated: if the threshold value is too low, then the unnecessarily remaining background pixels are added to the segmentation result, and if the threshold is too high, the thin, low-intensity capillaries disappear from the ends of vessels.

Solving this problem a recursive region growing algorithm [14] was applied. In the pre-processed image the objects with highest intensity contain to blood vessels or microaneurysms. This property of images is taken into account. As a starting point the pixels with maximal intensity are used, then those neighbouring pixels are assigned to the region, whose intensity

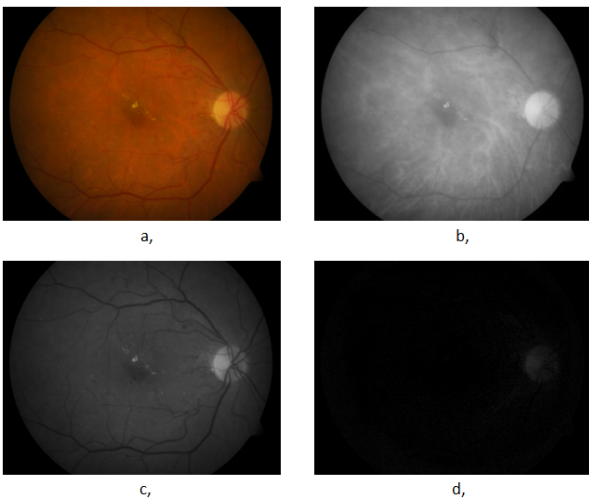


Fig. 3. Several color channels of an image. (a) original image, (b) red channel of (a), (c) green channel of (a), (d) blue channel of (a).

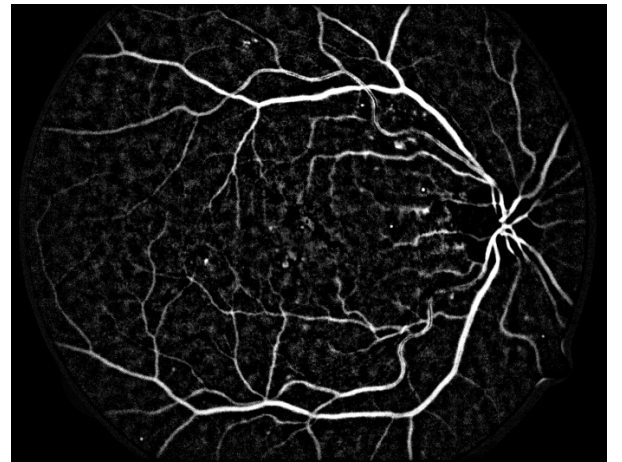


Fig. 4. The result of CLAHE, tone improvement and contrast stretching.

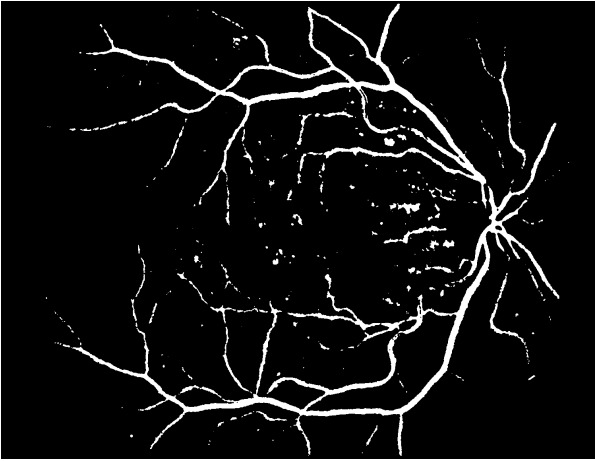


Fig. 5. The result of the recursive region growing algorithm.

is more than a pre-defined threshold. This process is applied while exists proper neighbouring pixel. For the application of this method two important parameters has to be chosen: first is the minimal intensity levels of starting points, and the second is the mentioned pre-defined threshold value. In the former an interval has to be given. It is important because of the raggedness of the vessel pixels. In recent state of our project the threshold values are determined manually.

In the achieved image (see Figure 5.) only the supposed microaneurysms and blood vessel can be found. This image is further analysed by a region area based picking method. Each region is checked based on its area, and the image is garbled into two parts. The regions that are larger than a manually specified area size are got into an output image, and smaller ones into another. It achieves two result images: one for the segmented blood vessels, and other for the microaneurysms.

IV. CLASSIFICATION

Based on a consensus all circular objects can be considered as microaneurysms, if its diameter is less than the cross-section of the largest blood vessel. So our task is divided into two parts: firstly, it is necessary to determine the cross-section of the largest blood-vessel, and then has to be checked the circular shape of the found objects.

A. Determination of the largest cross-section

To detect the largest cross-section of blood vessels a special algorithm was used. Our experiments revealed that the largest cross-section can be found in the most extensive objects in the image of blood-vessels. Thus, as a first step a skeleton is produced from the greatest region. From the pixels of the skeleton lines are built up in 0° , 45° , 90° and 135° direction. The lines are increased until it intercepts the border of the blood-vessel in the binarized image of blood-vessels. An example can be seen in Figure 6.

Only those cross-sections were taken into account, whose perpendicular line segment at least three times longer than the



Fig. 6. Determination of the largest cross-section with line segments.

length of the cross-section. It ensures that the actual cross-section is a real cross-section, and belongs to an elongated blood vessel, rather than a vessel turnout. These potential cross-sections are picked into a list, and the maximum value is selected for further calculations.

B. Checking of circular shape

As a next step of classification, a similar algorithm was used as a filtering. Also lines were place onto the skeleton of possible microaneurysms, then these line segments were increased until the object borders. The lengths at the individual objects were checked, to be approximately equal, which ensures the circular shape of the examined object.

Using this selection algorithm the result image contains the potential microaneurysm candidates considering their size and shape. In Figure 7. the microaneurysm candidates are noted by red closed curves.

V. EXPERIMENTS

The *diabetr1* database [2] is an image collection produced to testing detection of diabetic retionatphty algorithms. The database consists 89 images, 84 of them contains microaneurysms. According to experts who have carried out the

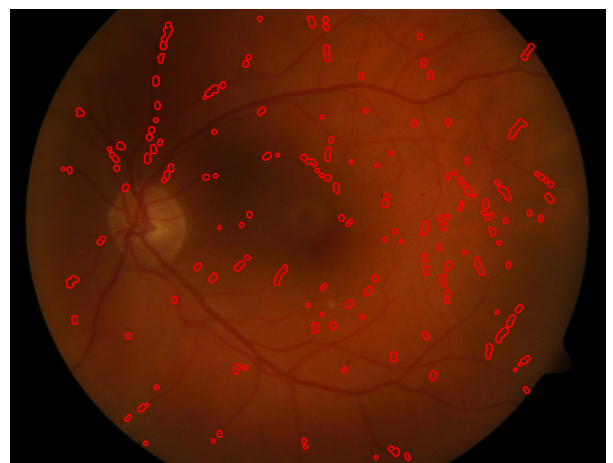


Fig. 7. Microaneurysm candidates are noted by red boundaries in the original input image.

TABLE II
RESULTS OF MICROANEURYSM DETECTION

Ratio of found microaneurysms	# of images with > 50% hit ratio	# of images with > 60% hit ratio
47%	9	4

processing of images, the residual images do not contain any signs that may indicate disease. The images were taken with 50° angle of incidence using digital fundus camera. The evaluation was performed by four independent experts.

The expert noted microaneurysms, hemorrhages and the areas belonging to exudates in the images. For each found object a confidence level were assigned to. The used confidence levels (less than 50%, more than 50% and nearly 100%) shows the correctness of notations.

Our algorithm was tested with 30 randomly selected images of the database. Table II presents our results. The ration of found microaneurysms is nearly 50%. We examined the number of those images where the hit ratio is more than 50% and 60% as well.

VI. CONCLUSIONS

The implemented algorithm is able to detect microaneurysms in digital fundus camera images. Based on the test results several further improvement is possible to increase to detection ratio.

During pre-processing the green channel of the input image was selected. This decision looks very effective, because all important information can be found well in this color channel.

For further usage of region segmentation the so-called CLAHE method was used. This method requires a few further change, because to many details were enhanced, and we could not exclude these pixels at the classification step. With fine-tuning of CLAHE, or usage of other contrast enhancing method expectedly better results will be achieved.

To estimate the background median filtering was applied, and this is proved suitable, because the important edges remained sharpen after filtering too. The disadvantage of this process the very time-consuming property. It can be fasten if smaller kernels or parallel computation will be used [15].

The result of two contrast enhancements was an image, with sharp important details, but the insignificant informations were strengthened too.

The applied region growing algorithm needs manual parameter settings, but the later automation can be solved.

The classification phase can be expanded with more criteria, it can exclude the false positive results. The main problem of shape- and size-based detection is that the intensified background pixels were taken into account with too high weight.

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