Original article

Automatic detection of microaneurysms in colour fundus images

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\textbf{A R T I C L E  I N F O}

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\textbf{A B S T R A C T}

Purpose: We present the development of a tool for the automatic detection of microaneurysms and its clinical evaluation. The intention of this tool is to facilitate the diagnosis of diabetic retinopathy in general screening programs.

Method: The designed and developed tool consists of three stages of processing: (1) Obtaining of the basic image of eye with the retinal camera, inverted image on the green channel, and a high-pass filter of the image. This phase enhances the microaneurysms. (2) Detection of the candidates for microaneurysms, by means of an adaptive prediction filter and regions growth. (3) Selection, among the candidates, of whom microaneurysms must be considered to fulfil the criteria of circular shape, high intensity in the inverted green channel and contrasts with respect to the surrounding pixels.

Results: We selected to 20 retinal photographs of good quality and dimensions 600 × 600 pixels from patients with nonproliferative diabetic retinopathy. The ophthalmologists detected 297 microaneurysms in these images. The tool for automatic detection correctly located 252 microaneurysms, with a mean sensitivity of 89% and a false positives rate of 93%.

Conclusions: The results obtained seem to indicate that the tool developed will be very useful for its potential use in screening programs in primary care centres. On the other hand, more work is needed on the algorithm to decrease the rate of false positives.

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\textbf{Detección automática de microaneurismas en retinografías}

\textbf{R E S U M E N}

Propósito: Presentamos el desarrollo de una herramienta para la detección automática de microaneurismas y su evaluación clínica. El propósito de esta herramienta es facilitar el diagnóstico de lesiones diabéticas en programas generales de detección.


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Diagnóstico asistido por computador
Procesamiento de datos asistido por computador

Método: La herramienta diseñada y desarrollada consta de tres etapas de procesamiento: 1) Obtención de la imagen de fondo de ojo con el retinógrafo, inversión del canal verde y filtrado paso de alta de la imagen. Esta fase realiza los microaneurismas. 2) Detección de los candidatos a microaneurismas, mediante un filtrado de predicción adaptativo y un crecimiento de regiones. 3) Selección, de entre los candidatos, de los que deben considerarse microaneurismas por cumplir con los criterios de: forma circular, intensidad alta en el canal verde invertido y contraste respecto a los píxeles de alrededor.

Resultados: Se seleccionaron 20 retinografías de buena calidad y dimensiones 600 × 600 píxeles de pacientes con retinopatía diabética no proliferante. Los oftalmólogos detectaron un total de 297 microaneurismas en estas imágenes. La herramienta de detección automática localizó adecuadamente 252 microaneurismas, con una sensibilidad media del 89% y una tasa de falsos positivos del 93%.

Conclusions: Los resultados obtenidos parecen indicar que la herramienta desarrollada podría ser muy útil para su potencial utilización en programas de detección en los centros de asistencia primaria. Por otro lado, es necesario seguir trabajando en el algoritmo para disminuir la tasa de falsos positivos.

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Introduction

The quantitative assessment of the number of microaneurysms (MA) is a good indicator of diabetic retinopathy (DR) progression. However, a manual comparison of the various time sequence images of patients is a time-consuming endeavour for the specialists, making it desirable to have a tool enabling automatic detection and assessment. In addition, said tool would be very useful to assist primary healthcare diagnostics.

An important number of engineering publications address this issue. The majority of these publications focus on the detection of MA in fluorescein angiographs. Øien and Osnes were the first to detect MA in color Images. Thereafter, various researchers have continued to publish work in this field.

This paper proposes a new technique for the automatic detection of MA, based on the use of adaptive prediction filters and growth of regions.

Subjects, material and methods

Thirty retinographs with good image quality were utilized from the Early Diabetic Retinopathy Detection Program of the Health Office of the Andalucía administration. Said images were taken with non-midiratic retinographs in patients with slight and moderate nonproliferative diabetic retinopathy and free of white diabetic lesions. Ten retinographs were utilized to prepare the algorithm and 20 to validate it.

Fig. 1 illustrates a flow chart of the method. In the figure, the tool comprises 3 processing stages: (1) preprocessing, (2) detection of candidates for MA, and (3) selection of the candidates to be considered as MA. The following sections describe these 3 processing stages.

Preprocessing Stage

The objective of this stage is to prepare the image for subsequent treatment, isolating the images having characteristics which are not inherent to the ocular fundus, such as illumination and contrast. This stage can be divided into the following steps:

1) Green channel inversion: as described by Walter et al. of the 3 color planes the green channel is the one containing the most relevant information (G). This claim is submitted to an inversion of the grade levels to obtain the negative of the green plane. This inversion is required to show MA with greater clarity. Fig. 2 depicts an example of this image.

2) High pass filtering (HP): this step consists in applying a high pass filtering to the green channel inversion to obtain a new image which emphasizes the pixels having values very different from adjacent pixels wide and those

Fig. 1 – Microaneurysm detection algorithm flow diagram.
having a homogeneous value will take up values close to zero. High pass filtering emphasizes image details.\textsuperscript{12} 

(3) Contrast enhancement: the objective of this operation is to increase the dynamic range of the image, that is to enhance its contrast by separating levels having similar intensity. 

(4) Top-hat morphological filtering: in this step the vascular tree is removed. To achieve this, this filtering depends on the shape (morphological filtering) and is able to differentiate between circular shapes (microaneurysms) and curved lines that can be simulated as a succession of straight sections (vascular tree).\textsuperscript{12} 

After the above steps have been completed, the image is ready for the detection of microaneurysms.

\textbf{Detection stage}

The objective of this stage is to obtain dots –seeds– on the basis of which the subsequent stage will be applied to obtain microaneurysm candidates. 

In order to detect the seeds a 2D linear prediction algorithm is utilized (Burg algorithm).\textsuperscript{13,14} Its operation can be summarized as follows: the algorithm processes every pixel of each image row, predicting the value of the following pixel to be processed on the basis of the value of its adjacent pixels. A prediction error exceeding a threshold in any pixel signals this as a unique dot (possible microaneurysm). For a pixel to be labeled as a seed, in addition to the condition that the prediction error exceeds a threshold, the pixel must have at least one adjacent pixel which has also been determined as a unique point. This is done in order to avoid isolated dots from being labeled as microaneurysms.\textsuperscript{15–17} 

\textbf{Segmentation stage}

The objective of the segmentation stage consists of obtaining a set of pixels (region) which make up prospective microaneurysms. To achieve this objective, the method utilized is the growth of regions by addition of pixels with stop conditions.

Regions are grown on the basis of the seeds obtained in the preceding stage. 

The segmentation stage is very important because its result determines the subsequent classification of prospective microaneurysms as the form of the segmented regions is a fundamental characteristic for said classification and in addition it engages considerable computer resources. 

The operation is as follows: for each seed an environmental verification is made, known as search environment, to determine whether adjacent pixels are also seeds belonging to the same region. The purpose of this operation is to establish a mean intensity value and local deviation of adjacent seed pixels. With these values, a threshold is set up to include in the region additional adjacent non-seed pixels that may belong to the same region. This threshold is also utilized as a stop condition. To add non-seed pixels to a region an additional environment is used, known as aggregation environment, in which a search is carried out for pixels having intensity values exceeding the threshold. As non-seed pixels are being added, they are considered to be seeds in order to continue the search. 

Said threshold is entirely local and in addition it is highly variable because every time one pixel is added to the region the entire region is recalculated. 

\textbf{Final microaneurysm selection stage}

Upon completion of the segmentation stage, the resulting regions are classified to differentiate genuine microaneurysms from prospects. This stage consists in an empirical classification process based on the extraction of 3 characteristics or descriptors: intensity (I), size (T) and form of the lesion (F). The intensity criterion is based on the local difference between the mean intensity of the overall region and the mean intensity of the region surrounding the prospective pixel. The size criterion is only the number of pixels making up the prospect. The form criterion consists of comparing the prospect form to a Gaussian 2D form. Each prospect may fulfill or not all of these criteria, with a 1 being assigned if a criterion is fulfilled and 0 if it is not. In order to decide whether a
prospect is a genuine microaneurysm the following equation is applied:

$$\frac{1}{I} + \frac{1}{T} + \frac{2}{F} \geq 3$$

It can be seen that the form characteristic has greater weight when determining whether a prospect is a microaneurysm or not.

**Results**

Twenty good-quality retinographs with a size of 600 × 600 pixels were selected on the basis of detail clarity, with a predominance of reddish diabetic lesions (microaneurysms and hemorrhages). Overall, ophthalmologists detected 297 microaneurysms in the 20 images. Of these, the automatic detection tool identified 252 microaneurysms, yielding a mean sensitivity of 89% and a false positive rate of 93%.

Table 1 shows the database results obtained for the 20 images.

<table>
<thead>
<tr>
<th>Image</th>
<th>S</th>
<th>PPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>0.89</td>
<td>0.95</td>
</tr>
<tr>
<td>Image 2</td>
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<td>0.94</td>
</tr>
<tr>
<td>Image 3</td>
<td>0.92</td>
<td>0.94</td>
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<tr>
<td>Image 4</td>
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<td>0.96</td>
</tr>
<tr>
<td>Image 5</td>
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<td>0.95</td>
</tr>
<tr>
<td>Image 6</td>
<td>0.82</td>
<td>0.81</td>
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<tr>
<td>Image 7</td>
<td>0.88</td>
<td>0.91</td>
</tr>
<tr>
<td>Image 8</td>
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<td>0.91</td>
</tr>
<tr>
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<tr>
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<tr>
<td>Image 13</td>
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</tr>
<tr>
<td>Image 14</td>
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<td>0.92</td>
</tr>
<tr>
<td>Image 15</td>
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<td>Image 16</td>
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<tr>
<td>Media</td>
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<td>0.93</td>
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</table>

S: sensitivity; PPV: positive predictive value.

**Discussion**

The inclusion of new technologies in clinic is an increasingly extended practice. An early diagnosis of diabetic retinopathy requires regular ocular fundus assessments of the diabetic patients by means of ophthalmoscopy and/or retinographs.

One of the key factors for early diabetic retinopathy detection is the emergence of microaneurysms. Regular assessment of the amount of microaneurysms provides an indication of the severity of the disease. Counting microaneurysms is a laborious and time-consuming chore for the clinician and therefore a diagnostic aid tool would be of great help.

Even though in recent years publications have appeared on the automatic detection of microaneurysms,3–7 very few have focused on detection by means of retinograph images.8–12 This paper presents a new algorithm for detecting MA in retinographs. The system features high sensitivity (89%) even though the number of false positives is high. Future lines of work in this endeavour could include the reduction of the false positive rate improving image preprocessing, more resized vascular tree detection and the use of neuronal networks for the final classifications of MA prospects.

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**Conflict of interest**

The authors have no conflict of interest to declare.

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**References**


