Automatic Detection of Diabetic Retinopathy Based on the Presence of Micro-Aneurysms: Barriers to the Translation from Research to Clinical Practice

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Diabetic retinopathy (DR) is a progressive disease which is the most common cause of blindness and early detection of this disease can limit vision loss. Retinal image grading is crucial for the prevention of visual loss but it is also a time consuming task. The Micro-aneurysm (MA) is the first sign of DR. The automatic detection of Micro-aneurysms (MAs) is an important and challenging research problem. This work presents an analysis of the failure modes of current automatic MA detection algorithms. It shows that such algorithms are confused by vascular structures. A method to improve algorithm performance by discarding vascular structures is proposed and analysed.

**Keywords:** diabetic retinopathy; microaneurysms; failure modes; vascular structures;

1. Introduction

Diabetic Retinopathy (DR) is a complication of diabetes in which high blood glucose concentration damages small blood vessels in the retina. It progresses without any noticeable symptoms until damage occurs. In many cases such damage cannot be reversed, so early detection and treatment of DR is crucial. However, it is time consuming for a human expert to grade retinal images. Typically 70% of these images are healthy [1], so the automatic detection of disease in images based on the detection of MAs is an interesting possibility and has been the subject of previous studies [2]. MA detection algorithms are confused by the effect of noise generated by uneven illumination, vascular structures, and other retinal disease features [3]. Here, the possible improvement in the performance of MA detection when vascular structures are disregarded is investigated.

2. Method and Results

Current automatic MA detection algorithms use image pre-processing, thresholding and region analysis. In this work, research is carried out by using a small annotated 10-image dataset randomly selected from a published database [4]. The threshold is initially set at 30% maximum intensity, at this level, all of the important retinal features, including all the MAs, are identified as regions. A total of 11674 regions are then classified using a support vector machine (SVM) based on features derived from the gray level co-occurrence matrix and the run-length matrix. This gives rise to 1216 false positives and 92 true positives. Table 1 shows examples of the failure modes of this procedure. To mitigate this low specificity, the number of regions is first reduced by increasing the initial threshold. Typically, an image with more than 3 MAs is usually defined as DR image. As analysed in [5], the best human expert performance in detecting abnormal retinal images is a detection
probability of 0.86 (a sensitivity of 86%). The minimum sensitivity, IS, for the detection of individual MAs level may be calculated from \((1 - IS)^2 = 1 - 0.86\), where IS represents the sensitivity requirements to detect individual MA. The result is 0.48, corresponding to a sensitivity of 48%. By increasing the initial threshold to 65% of maximum intensity, the number of regions falls from 11674 (93 true MAs) to 1798 (72 true MAs). After feeding these regions into the classifier, there are 189 false positives and 71 true positives. In order to further mitigate the false positives, the regions within 5 microns of blood vessels are then removed. Examples of MAs near blood vessels are shown in table 2. The number of regions is further reduced from 1798 to 641. The final result of this method is 62 false positives and 47 true positives after the same classifier.

Table 1: examples for false positives in different categories

<table>
<thead>
<tr>
<th>Vessel gap</th>
<th>Vessels crossing</th>
<th>Dark pigment</th>
<th>Other feature</th>
<th>Uneven illumination</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Table 2: examples for MA in different appearance

<table>
<thead>
<tr>
<th>MAs candidate near vessels</th>
<th>MAs candidate in cluster (periphery)</th>
<th>MAs candidates in Cluster (central)</th>
<th>Special case</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
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3. Conclusions

The fact that early stages of DR are associated with several MAs allows the feature selection threshold to be increased, thereby increasing the specificity whilst maintaining an acceptable sensitivity. A further improvement in specificity is obtained by using the proximity to blood vessels as a constraint. However in this small study there are still 6 false positives per image, so all 10 images in the dataset are classified as diseased. Further performance improvements in automated detection of MAs are required before this technique could be useful in clinical practice.

References:


