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A novel automatic image processing algorithm for detection of hard exudates based on retinal image analysis

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Abstract

We present an automatic image processing algorithm to detect hard exudates. Automatic detection of hard exudates from retinal images is an important problem since hard exudates are associated with diabetic retinopathy and have been found to be one of the most prevalent earliest signs of retinopathy. The algorithm is based on Fisher's linear discriminant analysis and makes use of colour information to perform the classification of retinal exudates. We prospectively assessed the algorithm performance using a database containing 58 retinal images with variable colour, brightness, and quality. Our proposed algorithm obtained a sensitivity of 88% with a mean number of 4.83 ± 4.64 false positives per image using the lesion-based performance evaluation criterion, and achieved an image-based classification accuracy of 100% (sensitivity of 100% and specificity of 100%).

Keywords: Diabetic retinopathy; Hard exudates; Image processing; Retinal images

1. Introduction

Diabetic retinopathy (DR) is the most common cause of blindness and vision defects in developed countries [1]. 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, fundus image enhancement [2–4], and monitoring [5]. Of special significance are automatic image analysis algorithms designed to detect hard exudates (HEs) [6]. HEs have been found to be the most specific markers for the presence of retinal oedema, the major cause of visual loss in non-proliferative forms of DR [1]. Additionally, HEs are one of the most prevalent lesions during early stages of DR [1].

Automatic algorithms for HE detection are required in a variety of applications including the design of complete systems for automatic processing of retinal images. Several techniques have been developed for HE detection in fundus images based on a variety of techniques [6]. These techniques include the usage of image contrast and brightness analysis [7–13], Bayesian classifiers [14,15], and neural networks [16,17].

In this paper, we propose a novel automatic image processing algorithm for detection of HEs based on retinal image analysis. The algorithm employs statistical recognition and colour information to detect retinal exudates. Our proposed algorithm does not require user initialization and is robust to the changes in the appearance of retinal fundus images typically encountered in clinical environments.

In Section 2, we describe the exudates detection algorithm in detail. Sections 3 and 4 report the performance results, and Section 5 discusses the contributions and limitations of the algorithm.

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2. Hard exudates detection

Our proposed algorithm for HEs detection is composed of four main stages: (1) image preprocessing and enhancement, (2) feature extraction, (3) classification, and (4) postprocessing. In the first stage, the image is enhanced to obtain adequate illumination normalization and contrast. Following this step, the algorithm extracts dynamical training sets from each image. Next, the algorithm classifies the pixels using a Fisher's linear discriminant. Finally, a postprocessing technique is applied to distinguish HEs from cotton wool spots (CWs) and other artefacts.

2.1. Preprocessing stage

The preprocessing stage is crucial to the algorithm success due to the intrinsic characteristics of the retinal images. For instance, due to the strong correlation between skin pigmentation and iris colour, the colour of fundus from different subjects is typically unique.

Additionally, retinal images are often poorly contrasted. The contrast of fundus images diminishes as distance of a pixel from the centre of the image increases. The uneven illumination raises the intensity levels in the regions near the optic disk (OD) but gradually reduces the brightness when distance to the OD is increased. All these features have a significant impact on the detection of retinal lesions, especially HEs.

Colour normalization and contrast enhancement of the fundus photographs are needed before starting exudate detection. Instead of applying grey-scale techniques independently to each colour component, our algorithm uses a modification of the RGB model to obtain colour normalization and contrast enhancement resulting in a set of new $(R_{mod}, G_{mod}, B_{mod})$ component as follows:

$$\begin{aligned}&(R,\ G,\ B) \rightarrow (Y,\ I,\ Q)\\&Y_{mod} = aY + bI + cQ\\&(Y_{mod},\ I,\ Q) \rightarrow (R_{mod},\ G_{mod},\ B_{mod}).\end{aligned} \tag{1}$$

where (R, G, B) are the three components of the original RGB model, (Y, I, Q) the components of the YIQ model and $\rightarrow$ defines the conversion of one colour space into another [18]. This transformation avoids the problems associated with applying grey-scale methods to each of the components due to the high correlation between components [19]. In this transformation a, b and c are parameters which depend on the characteristics of the images. They are selected to reduce the local luminance variability (σ_μ) throughout Y_{mod} and increase the mean contrast levels (μ_σ and μ_c) within it [4]. Applying the parameters $[a, b, c] = [1.5, -1, -1]$, the standard deviation of the local luminosity σ_μ in Y_{mod} decreases 6.10% compared to the original luminance component whereas the contrast levels μ_σ and μ_c increase 25.17% and 24.55%, respectively. The resulting image (Fig. 1(a and b)) shows an improvement in the overall colour saturation and in the contrast between lesions and background.

2.2. Feature selection and extraction

As HEs are mainly characterized by their colour, we used colour features to define the feature space. The selection of these features is a complicated task due to the variety of colour models. In order to select one of these models objectively we calculated a quantitative metric (J) to evaluate the performance of different colour spaces. The metric J estimates the class separability of exudate and non-exudate pixels in different colour spaces using within-class and between-class scatter matrices [20], as follows:

$$J = \mathrm{trace}\left(\frac{S_{\mathrm{b}}}{S_{\mathrm{w}}}\right) \tag{2}$$

where S_{b} and S_{w} are the between-class and within-class scatter matrices, respectively. A higher value of J indicates that the classes are more separated while members within each class are closer to each other. Applying this metric to several colour models, we have obtained the highest value for the new model $\mathrm{R_{mod}G_{mod}B_{mod}}$ (Table 1). Therefore, the proposed modification of the RGB model is the most suitable colour model for our retinal image analysis. A three-dimensional feature vector $\boldsymbol{X}$ is defined for each pixel made up of its components in the $\mathrm{R_{mod}G_{mod}B_{mod}}$ model.

Two training sets representative of our classification problem have to be selected: a non-exudate and an exudate sets. When the training sets are obtained manually, only a group of images are used to extract them. Due to the large intra-class variability among images, even after the preprocessing stage, these datasets are not representative of the characteristics of all the images. Our proposed algorithm overcomes this problem by automatically extracting several training sets from each image, avoiding manual segmentation.

For each image, the exudate training set is made up by pixels belonging to small isolated exudates. Their characteristics can represent the rest of exudates in the image. Additionally, this type of exudates can be found in all the fundus images with HEs, even in the earliest stages of DR. The exudate training set is obtained carrying out a coarse segmentation of the image. First, exudate edges in the image are enhanced applying Frei–Chen operator [21], which highlights the edges

Table 1
Class separability quantitative metric

Color model	RGB	HSI	YIQ	YCbCr	Lab	Luv	$\mathrm{R_{mod}G_{mod}B_{mod}}$
J	2.91	2.98	2.91	2.92	2.99	2.49	4.14

Quantitative analysis of class separability of exudates and non-exudates pixels using a manually and randomly segmented dataset of 1487 exudates pixels and 1873 non-exudates pixels.