Drusen Detection based on Scale-space with Feature Stability

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Abstract

This paper proposes a novel segmentation technique for drusen detection in retinal fundus images based on the scale space approach endowed with feature stability. To select significant blobs representing drusen, the stability of the features of scale-space blobs is taken into account in addition to conventional blobs' lifetime. The algorithm was tested with over 20,000 blobs from 26 retinal images and the results show that the method can detect variable size and variable shape drusen efficiently with Positive Predictive Value over 95%.

1 Introduction

Age-related macular degeneration (AMD) is a progressive disorder of the central retina, or macula, found in adults over the age of 50. The macula is responsible for sharp, clear central vision and the ability to perceive colours. Because AMD will cause no pain so patients never notice any change in their eyes until they cannot see clearly. Patients may only have blurred vision or slight visual distortion and in the worst cases, AMD results in either partial or complete loss of central vision, making reading, driving or even recognizing people impossible.

The presence of drusen, tiny yellow deposits in the retina is one of the most common early signs of AMD. Over a period of time, drusen slowly develop their sizes, shapes, and numbers. The ophthalmologists use these features as keys to classify the severity of AMD and to give appropriate treatment to patients. Automatic drusen detection can become very helpful for early drusen screening process.

There are several proposed drusen detection algorithms. P. Checco et al. [1] proposed a Cellular Neural Network-based algorithm which aims to enhance drusen in monochromatic red-free fundus image. For detecting drusen, they used an adaptive segmentation, an improved method of CNN algorithm [2]. K. Rapantzikos and M. Zervakis [3] proposed local histogram method to identify an appropriate local threshold for segmenting each

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region of drusen. Simple morphological operations, such as dilation and erosion, cannot be used directly since the drusen do not have a precise shape or size[4-5]. L .Brandon et al. [6] proposed an automatic drusen detection method using multi-level analysis. A fuzzy logic approach was also used for drusen detection [5]. To produce high accuracy drusen segmentation results, most techniques mentioned earlier require prior information about drusen such as intensity, colour and shape to specify appropriate parameters, e.g., intensity threshold and morphological window sizes. However, optimizing these parameters is very challenging since the retinal images have variation in light conditions and a wide variety of the shape and the size of the drusen. Even these parameters have been well adjusted using a training set, they will be robust and efficient as applied to only a test set with similar characteristics (contrast, light conditions, etc.).

Since the appearance of drusen is variable and difficult to predict, we take advantages of scale space algorithm, presented by Lindeberg [7-8], to develop a scheme for automatic drusen detection. Without prior knowledge of the region of interest, the scale space analyses an input image by blurring it several times using different scale parameters and detecting local maxima with extent, called grey-level blobs. The relationship of blobs between different scales can be presented by a scale-space blob tree. In the absence of further information, the significance of a blob can be measured using its lifetime. Blobs representing the regions of interest can be selected from those with high significance. The algorithm has been used to localize the optic disc [9] and detect variable size objects without prior information [10]. The detected results show that the algorithm is very efficient and robust even applied on variety of input image including low contrast and noisy images.

This paper presents an algorithm for drusen detection based on scale-space approach combined with feature-based analysis. In blob linking step, we define three criteria for drusen candidate selection based on feature stability and lifetime of the blobs.

2 Proposed Methods

2.1 Scale Space Representation

In scale space, a multi-scale representation of an image can be generated by convolving the image, f(x, y), with a series of Gaussian smoothing. Given an image, I, the output at scale σ of the image is $L(\sigma) = g(\sigma)*I$ where $g(\sigma)$ is the Gaussian kernel. A scale parameter, σ, of the kernel is gradually increased to obtain smoothed images in various scales. The increment of the scale parameter results in suppressing insignificant details while prominent structures tend to remain in coarser scales. Constructing several scales aims to analyze the behavior of the image structures under blurring. Throughout the process, the Gaussian smoothing simplifies the image without producing new spurious structures. Smaller blobs in finer scale may disappear or merge to other close blobs to form larger one in the next coarser scale. The blurring process will stop when the whole image eventually contains only one blob.

After extracting blobs from each scale, blobs between adjacent scales having corresponding locations will be linked as a binary tree to form a scale-space tree (as shown in Figure 1(a)). Suppose there are six scales and $t_1 – t_6$ denoted the finest to coarsest levels. Note that scale intervals can be different resulted from the refinement process. Each node represents a blob extracted at a specific scale. An edge connecting the two blobs indicates a direct spatial relationship between them. For example, b_2 at scale t_1 becomes b_{11} at scale t_2. b_{20} and b_{21} merge into blob b_{25}.

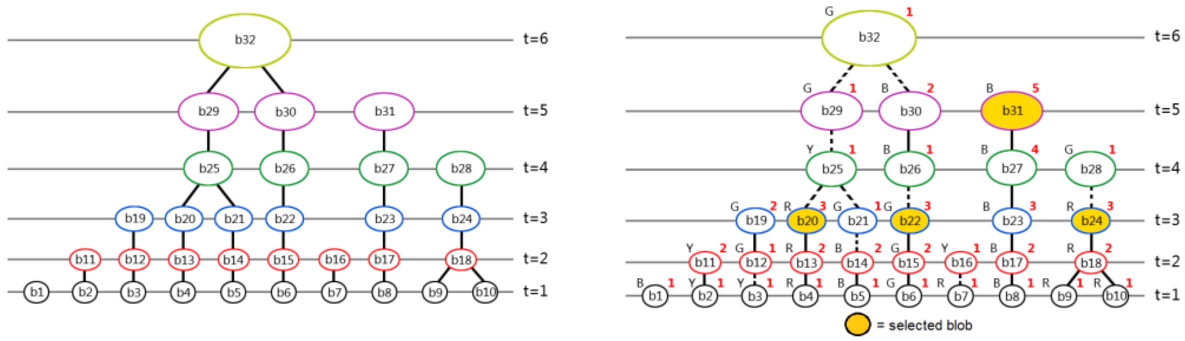
A blob can be either meaningful or meaningless component. The importance of each blob has to be, then, specified. If a blob stays for a long period in the scale space blob tree, it can be assumed to be important. Traversing the scale-space blob tree, yields the candidate objects in the original image.

2.2 Blob Significance Evaluations

Because the purpose of using scale space is to extract important structures in the image based on their appearance and significance of blobs in the scale space representation, we have to set some criteria for comparing significance of blobs between different scales. In other words, we need to judge which one should be regarded as more significant than others. With no other information, we assume that the important structures in the image stay longer over scales. The step used in this proposed method is discrete so our proposed and simplified blob lifetime, L, is defined by $L = t_D - t_A - t_{START}$ where t_D and t_A denote disappearance and appearance scales of the blob respectively and t_{START} is the time when the life count begins. t_{START} is introduced to eliminate the noise and unwanted tiny blobs.

2.3 Proposed blob significance measurement based on its feature stability

In this paper, the important attributes of a blob, such as a colour, texture, etc., are incorporated into the conventional blob linking process by defining the "strong" and "weak" links. The strong link connects between blobs having similar features while the weak link corresponds to an unstable feature and interrupts the life of the particular blob. Note that the links can be weighted depending on the degree of stability of the features defined below.



(a) (b)

Figure 1: (a) Cross sectional scale-space blob tree. (b) Example of blob selection by the proposed feature stability method.

By using the boundary of the blob as a mask, we can extract feature vector of the blob from the original image. Features can be represented by general descriptors of the colour, texture, etc.

We define the feature stability by

$$S = \frac{1}{dist(f, g)} \tag{3}$$

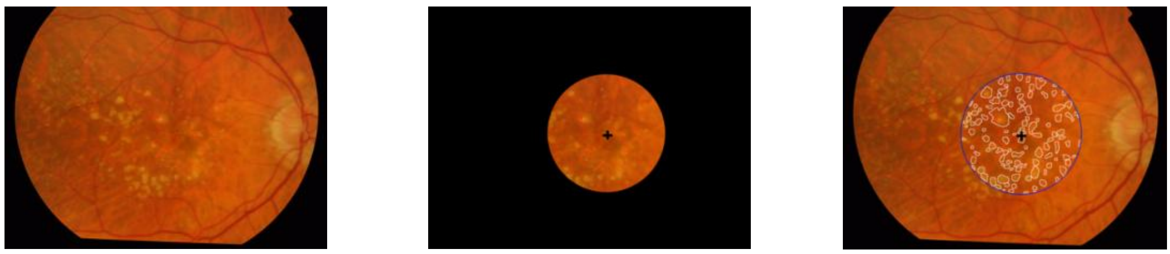
where $f = [f_1, f_2, f_3, ..., f_n]$ and $g = [g_1, g_2, g_3, ..., g_n]$ are feature vectors corresponding to two candidate blobs and $dist$ is an appropriate distance such as Euclidean distance or

Mahalonobis distance. Note that a distance with weights w_i can be used, such as, $dist(f, g) = \Sigma\ w_i\ dist(f_i,g_i)$ if the features have different significance. However In this experiment all the features have equal weight. Additionally the significance of the features may vary depending on the time step.

The feature stability approach is demonstrated in Figure 1(b). The feature vector consists of one nominal feature (colour) characterized by R, G, B and Y (as denoted on the top-left corner of the blob) and lifetime, denoted on the top-right corner.

3 Proposed Methods

The area occupied by drusen is very important information for severity grading. A standard grid template centred at the macula is overlaid onto the original image in order to provide diagnosis baseline for the ophthalmologists. The grid is adapted from the Early Treatment Diabetic Retinopathy Study [11]. The grid is manually put onto the image at the fovea (centre of macula) as shown in Figure 2 by an expert ophthalmologist. The drusen detection results will be shown within grid area only.



(a) (b) (c)

Figure 2: A circular grid superimposed onto the input image to scope the area of drusen detection.

(a)

(b)

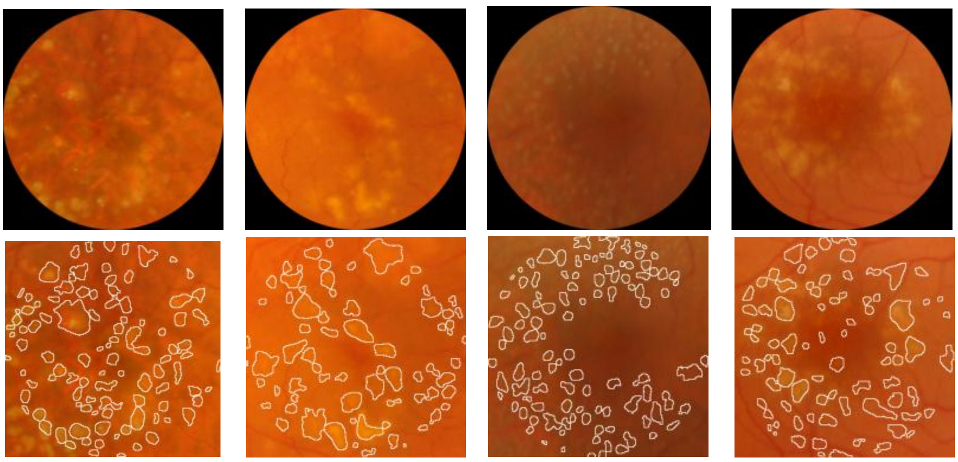


Figure 3: Example of drusen detection results. (a) input images (b) corresponding detection results.

The proposed algorithm was tested with 26 retinal images taken at Eye Centre, St.Thomas' hospital London with image size of 768 x 576 pixels. Some of the detection results are shown in Figure 3. The results are then verified at pixel level against expert ophthalmologist hand drawn ground truth. From a total of 25,041 blobs in 26 images, the proposed algorithm yields Sensitivity of 87.31%, misclassified proportion of 3.41% and Positive Predictive Value of 95.83%.

4 Conclusion and Discussion

A novel approach for automatic drusen detection based on scale space and feature stability is proposed. The algorithm efficiently identifies drusen using both information of blobs' lifetime in scale space tree and blobs' feature stability with high accuracy. Feature stability across scales is used to prune the tree so the detection result with better accuracy can be achieved faster. The algorithm is robust that it can detect variable size and variable shape drusen without a priori information even though the shapes and sizes of multiple drusen are not uniform throughout the image. The algorithm is also flexible so that the feature vectors can be extended or modified to suit particular applications.

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