Information Sciences 296 (2015) 14–24

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Exudate segmentation in fundus images using an ant colony optimization approach

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ARTICLE INFO

Article history:
Received 3 January 2013
Received in revised form 20 October 2014
Accepted 27 October 2014
Available online 4 November 2014

Keywords:
Ant colony optimization
Exudate
Fundus image
Image processing
Multi-agent system

ABSTRACT

The leading cause of new blindness and vision defects in working-age people, diabetic retinopathy is a serious public health problem in developed countries. Automatic identification of diabetic retinopathy lesions, such as exudates, in fundus images can contribute to early diagnosis. Currently, many studies in the literature have reported on segmenting exudates, but none of the methods performs as needed. Moreover, several approaches were tested in independent databases, and the approach's capacity to generalize was not proved. The present study aims to segment exudates with a new unsupervised approach based on the ant colony optimization algorithm. The algorithm's performance was evaluated with a dataset available online, and the experimental results showed that this algorithm performs better than the traditional Kirsch filter in detecting exudates.

1. Introduction

Diabetic retinopathy (DR) is an eye disease associated with long-standing diabetes mellitus, which causes abnormalities in the retina. DR has become a serious public health problem in developed countries, since it is the leading cause of new blindness and vision defects in working-age individuals. In the initial stages of DR, patients are generally asymptomatic, but in the more advanced phase, they may experience symptoms that include distortion and blurred vision. Therefore, early detection of DR is crucial for preventing vision impairment and for effective treatment. The easiest method for analyzing the eye fundus in screening programs for preventing DR is digital color fundus photographs. They create a high-quality record of the fundus for detecting DR early signs and monitoring its progression. However, due to the growing incidence of diabetes in the population, ophthalmologists must examine a huge number of images. Therefore, developing computational tools that can assist diagnoses is of major importance.

Exudates are one of the earliest signs of DR. They indicate increased vessel permeability since they are plasma lipid and protein accumulations in the retina. In fundus images, exudates appear as shiny yellow–white dots with sharp borders. Exudates are frequently observed with microaneurysms, characteristic dark DR lesions. The problems in accurately detecting exudates in fundus images are noise presence, low contrast, uneven illumination, and color variation. Several approaches have been proposed in the literature to segment this type of lesion from color fundus photographs. Giancardo et al. [10] roughly divided the approaches into four categories: thresholding, morphology, region growing, and supervised methods.

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http://dx.doi.org/10.1016/j.ins.2014.10.059
0020-0255/

Thresholding methods are based on global or local gray-level analysis. For instance, Sanchez et al. [24] presented a thresholding method based on a statistical mixture model. This method was used on the enhanced image histogram to determine a dynamic threshold for each image. Then, a postprocessing technique based on edge detection using Kirsch's method was applied to distinguish hard exudates from other bright lesions.

Morphology methods consist of applying morphological operators to identify structures with specific shapes (such as vessels). These structures are then removed, and exudates can be selected [3,23,25,28,29]. Morphological operators are sometimes combined with other techniques such as contrast enhancement and clustering methods [3].

Region growing methods segment the image based on spatial gray-level contiguity. For instance, Li and Chutatape [15] used CIE Luv color space images and applied a region growing method proceeded by the Canny edge detector. Edge detection decreases the size of the regions and significantly decreases the computation time.

Supervised methods are the most common in the literature [7,8,10,12,20,21]. They consist of building a feature vector for each pixel or pixel cluster, to be classified with a machine learning approach into exudates or non-exudates. The features are based on the color, brightness, size, shape, edge strength, texture, and contextual information of pixel clusters. The machine learning methods commonly used are neural networks [8,21], support vector machines (SVMs) [7,10], linear discriminant classifiers [12,20], the Naïve Bayes classifier [10], and the random forest algorithm [32]. A hybrid classifier as an ensemble of a Gaussian mixture model and an SVM was proposed in [1].

The problem with supervised approaches is that numerous manually labeled data are needed. Ali et al. [2] created a retinal atlas image with a set of healthy fundus images and then detected the bright lesions by determining the chromatic differences between the atlas images and an image of a diseased eye.

The results for these approaches are summarized in Table 1. Unfortunately, the majority of these algorithms were tested in independent databases with different characteristics. Therefore, it is not possible to prove the approaches' capacity to generalize. Moreover, the results were quantified using different evaluation methods, which makes comparing the results difficult.

Table 1
Results and methodology categories of approaches in the literature.

Author	Method category	Results	Dataset
Walter et al. (2002)	Morphology	Sensitivity/predictive value pair of 92.8%/92.4% (per lesion)	30 Images: 15 with exudates
Li et al. (2004)	Region growing	Sensitivity/specificity pair of 100%/71 % (per image)	35 Images with exudates
Fleming et al. (2007)	Supervised	Sensitivity/specificity pair of 95%/84.6% (per image)	13 219 Images: 300 with exudates
Niemeijer et al. (2007)	Supervised	Area under ROC curve = 0.95; sensitivity/specificity pair of 95%/88% for detecting bright lesions of any type (per lesion)	300 Images: 100 with bright lesions and 200 without
Sanchez et al. (2008)	Supervised	Sensitivity of 88% and mean number of false positive per image of 4.83 ± 4.64 (per lesion); sensitivity/specificity pair of 100%/100% (per image)	83 Images: 25 for training and 58 for testing (36 with exudates)
Sopharak et al. (2008)	Morphology	Sensitivity/specificity pair of 80%/99.5% (per lesion)	60 Images: 40 with exudates
García et al. (2009)	Supervised	Sensitivity/predictive value pairs of 88.1%/80.7 % with MLP, 88.5%/77.4 with RBF, 87.6%/83.5% with SVM (per lesion) and sensitivity/specificity pairs of 100%/92.5% with MLP, 100%/81.5% with RBF, 100%/77.8% with SVM (per image)	117 Images: 50 for training and 67 for testing (40 with DR signs)
Ravishankar et al. (2009)	Morphology	Sensitivity/specificity pairs of 94.6%/ 91.1% (per pixel) and 95.7%/94.2% (per image)	516 Images: 345 with exudates
Sanchez et al. (2009)	Dynamic thresholding	Sensitivity/predictive value pair of 90.2%/96.8% (per lesion) and sensitivity/specificity pair of 100%/90% (per image)	106 Images: 26 for training and 80 for testing (40 images with exudates)
Osareh (2009)	Supervised	Sensitivity/specificity pair of 96%/94.6% (per image) and sensitivity/predictive value pair of 93.5%/92.1% (pixel level)	300 Images: 150 with DR signs
Welfer (2009)	Morphology	Sensitivity/specificity pair of 70.5%/98.8 % (per image)	DIARETDB1
Amel (2012)	Morphology	Sensitivity/predictive value pair of 95.9%/92.3%	50 Images from MESSIDOR
Giancardo (2012)	Supervised	Area under ROC curve between 0.88 and 0.94 depending on the dataset/features used	MESSIDOR; HEI-MED and DIARETDB1
Ali (2013)	–	Accuracy of 82.60% (per lesion)	HEI-MED
Akram (2014)	Supervised	97.3%, 95.9% and 96.8% for sensitivity, specificity and accuracy, respectively (per lesion)	MESSIDOR and HEI-MED
Zhang (2014)	Supervised	Area under ROC curve between 0.93 and 0.95 depending on the dataset/features used	MESSIDOR; HEI-MED and DIARETDB1