Computers in Biology and Medicine 63 (2015) 208–218

Contents lists available at ScienceDirect

Computers in Biology and Medicine

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

Local configuration pattern features for age-related macular degeneration characterization and classification

Muthu Rama Krishnan Mookiah [a,*], U. Rajendra Acharya [a,b,c], Hamido Fujita [d], Joel E.W. Koh [a], Jen Hong Tan [a], Kevin Noronha [e], Sulatha V. Bhandary [f], Chua Kuang Chua [a], Choo Min Lim [g], Augustinus Laude [h], Louis Tong [i,j,k,l]

[a] Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore 599489, Singapore
[b] Department of Biomedical Engineering, School of Science and Technology, SIM University, Singapore 599491, Singapore
[c] Department of Biomedical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia
[d] Faculty of Software and Information Science, Iwate Prefectural University (IPU), Iwate 020-0693, Japan
[e] Department of Electronics and Telecommunication, St. Francis Institute of Technology, Mumbai 400103, India
[f] Department of Ophthalmology, Kasturba Medical College, Manipal 576104, India
[g] School of Engineering, Ngee Ann Polytechnic, Singapore 599489, Singapore
[h] National Healthcare Group Eye Institute, Tan Tock Seng Hospital, Singapore 308433, Singapore
[i] Singapore National Eye Center, Singapore 168751, Singapore
[j] Ocular Surface Research Group, Singapore Eye Research Institute, Singapore 168751, Singapore
[k] Duke-NUS Graduate Medical School, Singapore 169857, Singapore
[l] Yong Loo Lin School of Medicine, National University of Singapore, Singapore 117597, Singapore

ARTICLE INFO

Article history:
Received 28 February 2015
Accepted 26 May 2015

Keywords:
Retina
Age-related macular degeneration
Fundus imaging
Local configuration pattern
Support vector machine

ABSTRACT

Age-related Macular Degeneration (AMD) is an irreversible and chronic medical condition characterized by drusen, Choroidal Neovascularization (CNV) and Geographic Atrophy (GA). AMD is one of the major causes of visual loss among elderly people. It is caused by the degeneration of cells in the macula which is responsible for central vision. AMD can be dry or wet type, however dry AMD is most common. It is classified into early, intermediate and late AMD. The early detection and treatment may help one to stop the progression of the disease. Automated AMD diagnosis may reduce the screening time of the clinicians. In this work, we have introduced LCP to characterize normal and AMD classes using fundus images. Linear Configuration Coefficients (CC) and Pattern Occurrence (PO) features are extracted from fundus images. These extracted features are ranked using *p*-value of the *t*-test and fed to various supervised classifiers viz. Decision Tree (DT), Nearest Neighbour (*k*-NN), Naive Bayes (NB), Probabilistic Neural Network (PNN) and Support Vector Machine (SVM) to classify normal and AMD classes. The performance of the system is evaluated using both private (Kasturba Medical Hospital, Manipal, India) and public domain datasets viz. Automated Retinal Image Analysis (ARIA) and STructured Analysis of the Retina (STARE) using *ten*-fold cross validation. The proposed approach yielded best performance with a highest average accuracy of 97.78%, sensitivity of 98.00% and specificity of 97.50% for STARE dataset using 22 significant features. Hence, this system can be used as an aiding tool to the clinicians during mass eye screening programs to diagnose AMD.

1. Introduction

AMD is a multi-factorial ocular disease caused by deterioration of cells in the macula (See Fig. 1b) [1]. It is one of the leading causes of central vision loss [2] in people aged over 50 years [3]. AMD is characterized by drusen, retinal pigmentation, CNV and atrophy of photoreceptors [4]. It has several risk factors viz. age, smoking, hypertension and family history [5–7]. Recent World Health Organization (WHO) report reveals that 8 million people are affected with severe blindness due to AMD [8]. Globally, United Nations (UN) estimates that 20–25 million people are having AMD [9] and this figure may increase to 196 million in 2020 and 288 million in 2040 [10]. According to the presence of clinical features, AMD is mainly classified into three stages viz. *early*, *intermediate* and *late* [1]. They are briefly explained below.

(i) *Early AMD* is characterized by the presence of drusen with a size of $\geq 15\ \mu m$ and $< 63\ \mu m$ in diameter. Also, it has

* Corresponding author. Tel.: +65 64607889.
E-mail address: mkm2@np.edu.sg (M.R.K. Mookiah).

http://dx.doi.org/10.1016/j.compbiomed.2015.05.019
0010-4825/

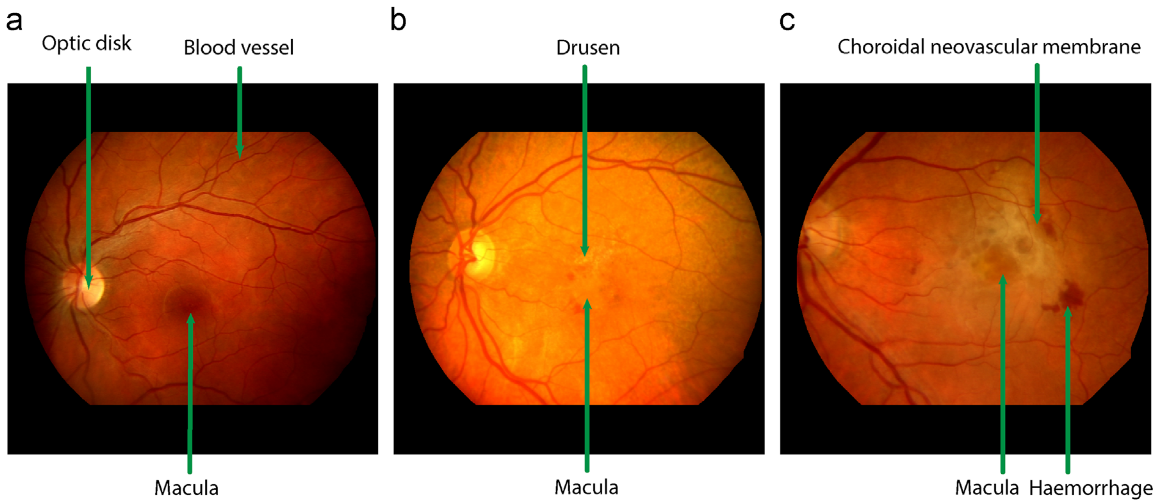

Fig. 1. Typical fundus images (from ARIA dataset): (a) normal, (b) dry AMD, and (c) wet AMD.

abnormal lesions viz. hyperpigmentations or hypopigmentations [1,11].

(ii) *Intermediate AMD* is graded due to the presence of medium sized i.e., ≥ 63 µm and < 125 µm drusen and pigment abnormalities [1,4]. The lesion is present around the macula (not in the centre) [1,11].

(iii) *Late AMD* is characterized with GA and CNV. It is categorized into two types viz. *dry* and *wet* [1] which are described below:
   (a) *Dry AMD* or non-neovascular AMD is characterized by the presence of drusen and GA in the centre of the macula (See Fig. 1b) [1,11]. Almost 90% of the vision loss is caused due to dry AMD [2]. There is no specific treatment method that may reduce the progression of late AMD [12].
   (b) *Wet AMD* is also known as neovascular AMD characterized by CNV [5]. Eyes affected with CNV may leak blood (See Fig. 1c) and the leakage is expressed as classic or occult [5]. The leakage can be diagnosed using fluorescein angiography and indocyanine green dyes [5]. Wet AMD is found in 10% of total macular degeneration cases [2]. Neovascular AMD can be treated using thermal laser photo-coagulation [5].

AMD can be diagnosed by identifying drusen from the retinal fundus images [13]. Automatic segmentation of drusen and its measurement is needed to automate the diagnostic process [14]. Hence, several authors have proposed AMD detection using automated drusen segmentation [15–27].

Brandon et al. [15] proposed multi-level analysis to isolate drusen from the retinal images. Their method obtained correct detection rate of 87.00%. But this method is susceptible to Optic Disc (OD) and blood vessel variations. Sbeh et al. [16] used mathematical morphology to segment bright spots. Shape, contrast and area criterion are used to segregate the drusen from these spots. However, performance measures of their method are not reported. Adaptive Local Thresholding (HALT) operator is used in [17] to segment drusen with vague boundary as well as small drusen and reported a sensitivity of 98.00%. Gaussian derivative filters and *k-NN* classifier is used in [18] to identify drusen and obtained a sensitivity and a specificity of 77.00% and 88.00% respectively. Their method is not effective to identify all drusen spots. Soliz et al. [19] used Independent Component Analysis (ICA) to detect drusen phenotypes and their method obtained an accuracy of 100% using only 12 fundus images. Amplitude Modulation (AM)–Frequency Modulation (FM) based multi-scale features is used in [20] to identify drusen and reported an Area Under receiver operator characteristics Curve (AUC) of 1. Their method is able to characterize slow varying intensities in the fundus images. Mexican hat wavelet and Support Vector Data Description (SVDD) are used to detect drusen from normal and AMD images. Their method is tested using seven images and reported 100% accuracy [21]. Liang et al. [22] proposed intensity based drusen segmentation approach and reported a sensitivity and specificity of 75.00%. Removal of blood vessel and location of macula are needed in their approach. Multi-resolution locally-adaptive segmentation method is proposed to segment drusen spots. Their method obtained a sensitivity of 95.00% and a specificity of 96.00% by selecting threshold manually [23]. Statistical modelling based drusen segmentation approach is used in [24] and reported an Area Under receiver operator characteristics Curve (AUC) of 0.99 and false positives are removed using post processing. Sobel operator and Gaussian function are used in [25] to segment drusen. Their method obtained a kappa agreement of 0.60. This thresholding method produced a large number of false positives. Optimal filter bank is developed in [26] to differentiate drusen and flecks. Their method obtained an AUC of 0.85. Cheng et al. [27] proposed BIF to detect drusen in the fundus images. Their method used Gabor functions to develop BIF and reported a sensitivity and a specificity of 86.30% and 91.90% respectively. The reported works in the literatures perform only drusen segmentation. They did not extend their method to detect AMD, except in [17,26]. Authors [17,26] segmented the drusen first and then detected the AMD class.

Further, inverse anomaly segmentation is proposed in [28] to identify AMD lesions and reported a segmentation accuracy of 90.00%. Case Based Reasoning (CBR) and Dynamic TimeWarping (DTW) methods are proposed in [13] to discriminate normal and AMD classes with a sensitivity of 86.00%. Inverse segmentation using statistical texture features is used in [29] to identify healthy and unhealthy areas from AMD images and reported an accuracy of 92.76% and 96–100% respectively. Spatial histogram and hierarchical image decomposition methods are developed to classify normal and AMD classes [11]. Their techniques obtained an accuracy of 74.00% and 100% using spatial histogram and hierarchical decomposition [11] respectively. Wavelet, GLCM, color, histogram based features and Weighted Frequent Sub-Graph Mining (WFSM) are used in [30] to classify normal and AMD classes. Their method achieved an accuracy of 99.90%. Zheng et al. [31] used tree based hierarchical decomposition and WFSM for automated detection of AMD and reported an accuracy of 99.60%. AM-FM based decomposition and statistical moments and histogram percentiles are used as features in [32] to discriminate