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Automated detection of age-related macular degeneration using empirical mode decomposition

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ABSTRACT

Age-related Macular Degeneration (AMD) is the posterior segment eye disease affecting elderly people and may lead to loss of vision. AMD is diagnosed using clinical features like drusen, Geographic Atrophy (GA) and Choroidal NeoVascularization (CNV) present in the fundus image. It is mainly classified into dry and wet type. Dry AMD is most common among elderly people. At present there is no treatment available for dry AMD. Early diagnosis and treatment to the affected eye may reduce the progression of disease. Manual screening of fundus images is time consuming and subjective. Hence in this study we are proposing an Empirical Mode Decomposition (EMD)-based nonlinear feature extraction to characterize and classify normal and AMD fundus images. EMD is performed on 1D Radon Transform (RT) projections to generate different Intrinsic Mode Functions (IMF). Various nonlinear features are extracted from the IMFs. The dimensionality of the extracted features are reduced using Locality Sensitive Discriminant Analysis (LSDA). Then the reduced LSDA features are ranked using minimum Redundancy Maximum Relevance (mRMR), Kullback–Leibler Divergence (KLD) and Chernoff Bound and Bhattacharyya Distance (CBBD) techniques. Ranked LSDA components are sequentially fed to Support Vector Machine (SVM) classifier to discriminate normal and AMD classes. The performance of the current study is experimented using private and two public datasets namely Automated Retinal Image Analysis (ARIA) and STructured Analysis of the Retina (STARE). The 10-fold cross validation approach is used to evaluate the performance of the classifiers and obtained highest average classification accuracy of 100%, sensitivity of 100% and specificity of 100% for STARE dataset using only *two* ranked LSDA components. Our results reveal that the proposed system can be used as a decision support tool for clinicians for mass AMD screening.

1. Introduction

Age-related Macular Degeneration (AMD) is a irreversible, chronic and multi-factorial ocular condition, identified by the presence of clinical features namely drusen, Retinal Pigment Epithelial Defect (RPED), Choroidal NeoVascularization (CNV) and Geographic Atrophy (GA) [1]. AMD is caused by ageing of cells in the macula region. It affects the people above the age of 50 years and may lead to blindness [1]. United Nations (UN) and World Health Organization (WHO) estimates 20–25 million people are affected worldwide and 8 million people have severe visual loss

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Table 1
Details of AMD grading [1–5].

	Early AMD	Intermediate AMD	Late AMD	
			Dry (non-neovascular AMD)	Wet (neovascular AMD)
Clinical features	– Drusen – RPED irregularities – Absence of choroidal vessels	– Drusen (see Fig. 1b) – GA (not in the macula centre)	Drusen and GA present in the centre of the macula (see Fig. 1c)	– RPED/neuroretinal atrophy – New vessel proliferation (CNV) (see Fig. 1c)
Symptoms	Asymptomatic	– Blurred or distorted central vision – Objects and straight lines appear as wavy – Eyes are sensitive to light		
Detection methods	– Dilated fundus examination – Visual acuity test – Amsler grid	Fluorescein angiography		
Treatment methods	No specific treatment available. Oral antioxidants may reduce the progression			Anti-Vascular Endothelial Growth Factor (VEGE) intravitreal injections

[2]. According to the presence of above mentioned clinical features AMD is mainly categorized into early, intermediate and advanced stages [3]. Further, advanced AMD is classified into *dry* and *wet* type. The clinical features, symptoms, detection methods and treatment options are described in Table 1.

Early stage of AMD shows no symptoms, however it can be detectable by the presence of drusen [4]. According to Wisconsin AMD grading [6] drusen is classified as per the size and boundary visibility. This work utilized Wisconsin AMD grading [6] to examine the fundus images of private dataset which is used in this study and the images are labelled as early, intermediate and late AMD by the clinical experts. Several works reported in the literatures proposed various AMD detection methods using drusen segmentation which are briefly explained in Table 2.

Most of the reported works in Table 2 concentrates on drusen segmentation except few studies [9,14,16,19]. The works in [9,14,16,19] uses drusen segmentation for automated detection of AMD. However, segmentation of drusen is a challenging task due to poor boundary visibility and other abnormal lesions [21]. Hence, few works [5,7,21–27] proposed image analysis and pattern classification techniques for automated screening of AMD. Hijazi et al. [21] proposed hierarchical decomposition and spatial histogram techniques for automated AMD screening and reported an accuracy of 74% and 100% respectively. Inverse segmentation method using statistical texture features is proposed in [22,23] to identify healthy and unhealthy region in AMD images. Their method obtained an inverse segmentation accuracy of 90% for unhealthy region [22]. The statistical segmentation in [23] obtained segmentation accuracy of 89.59%, 92.69% and 93.03% for small, medium and large degeneration [23] respectively. Instantaneous Amplitude (IA) and Instantaneous Frequency (IF) are used in [24] for the detection of drusen, pigmentation, GA and extended to

Table 2
Summary of drusen segmentation techniques [7].

Authors	Methods	Highlights/limitations	Segmentation performance
Sbeh et al. [8]	*h*-Maxima	Shape, contrast, area criterion used in post processing	Not mentioned
Brandon et al. [9]	Multi-level analysis	Susceptible to OD and blood vessel changes	Accuracy – 87%
Rapantzikos et al. [10]	– Multilevel histogram equalization – Histogram-based adaptive local thresholding	Drusen with undefined boundary can be segmented	– Sensitivity – 98% – Specificity – 99%
Niemeijer et al. [11]	– Derivative of Gaussian – *k*-Nearest Neighbour (*k*-NN) classification	Differentiates drusen, Hard Exudates (HE) and Cotton Wool Spots (CWS)	– Sensitivity – 77% – Specificity – 88%
Soliz et al. [12]	Independent component analysis	Tested on 12 fundus images only	Accuracy – 100%
Barriga et al. [13]	– Amplitude modulation – Frequency modulation	Instantaneous frequency provides high discrimination between drusen and vessels	Area Under receiver operator characteristics Curve AUC – 1
Freund et al. [14]	– Mexican hat wavelet – Support Vector Data Description (SVDD)	Tested on 7 fundus images only	Accuracy – 100%
Liang et al. [15]	Maximal region pixel intensity	Tested on 16 fundus images only	Sensitivity – 75%
Burlina et al. [16]	Multi-resolution pyramid decomposition	Intensity, colour and gradient knowledge is utilized	– Sensitivity – 95% – Specificity – 96%
Santos-Villalobos et al. [17]	Neyman–Pearson Lemma likelihood ration	Post processing needed	AUC – 1
Mora et al. [18]	– Image gradient – Gaussian modelling	Segment drusen even image with low contrast	Kappa agreement – 0.60
Quellec et al. [19]	Optimal wavelet filter designed using Haar	Discriminates microaneurysm, drusen and flecks	AUC – 0.85
Cheng et al. [20]	Biologically Inspired Features (BIF) derived using Gabor filters	Capture the *gist* of an image	– Sensitivity – 86.3% – Specificity – 91.9%