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Genetic algorithm based feature selection combined with dual classification for the automated detection of proliferative diabetic retinopathy

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ABSTRACT

Proliferative diabetic retinopathy (PDR) is a condition that carries a high risk of severe visual impairment. The hallmark of PDR is the growth of abnormal new vessels. In this paper, an automated method for the detection of new vessels from retinal images is presented. This method is based on a dual classification approach. Two vessel segmentation approaches are applied to create two separate binary vessel map which each hold vital information. Local morphology features are measured from each binary vessel map to produce two separate 4-D feature vectors. Independent classification is performed for each feature vector using a support vector machine (SVM) classifier. The system then combines these individual outcomes to produce a final decision. This is followed by the creation of additional features to generate 21-D feature vectors, which feed into a genetic algorithm based feature selection approach with the objective of finding feature subsets that improve the performance of the classification. Sensitivity and specificity results using a dataset of 60 images are 0.9138 and 0.9600, respectively, on a per patch basis and 1.000 and 0.975, respectively, on a per image basis.

1. Introduction

Diabetes mellitus is a disorder of sugar metabolism caused by an absolute lack of insulin or an insufficient action of insulin and hence is characterized by raised levels of glucose in the blood. High blood glucose levels (Hyperglycemia) can damage the vessels that supply blood to vital organs. Diabetic retinopathy (DR) is the resultant disorder affecting the retinal vasculature, leading to progressive retinal damage that can end in loss to vision and blindness [1]. DR is the most frequent cause of new cases of blindness among adults aged 20–74 years [2]. The problem is increasing in its scale, with diabetes identified as a significant growing global public health problem [3]. In the United Kingdom alone, three million people are estimated to have diabetes and this figure is expected to double in the next 15–30 years [4].

Diabetic patients are required to attend regular eye screening appointments in which DR can be assessed, with the intention of early detection of the disease to allow for timely intervention [5,6]. During these appointments retinal images are captured and Fig. 1 shows examples of such images. These images then undergo various stages of manual assessment by trained individuals [7]. This assessment can be a very time consuming and costly task due to the large diabetic population. Therefore this is a field that would greatly benefit from the introduction of automated detection systems [8].

The damage to the retinal blood vessels will cause blood and fluid to leak on the retina and form features such as microaneurysms, haemorrhages, exudates, cotton wool spots and venous loops [9]. With progression, the blockages and damage to blood vessels deprive areas of the retina with their blood supply. These areas of the retina send signals to the body to grow new blood vessels for nourishment. New vessels are the hallmark of proliferative diabetic retinopathy (PDR), which is the most advanced stage of DR. PDR poses a high risk of severe vision loss due to the fragile nature of the new vessels making them prone to bleed and cause pre-retinal

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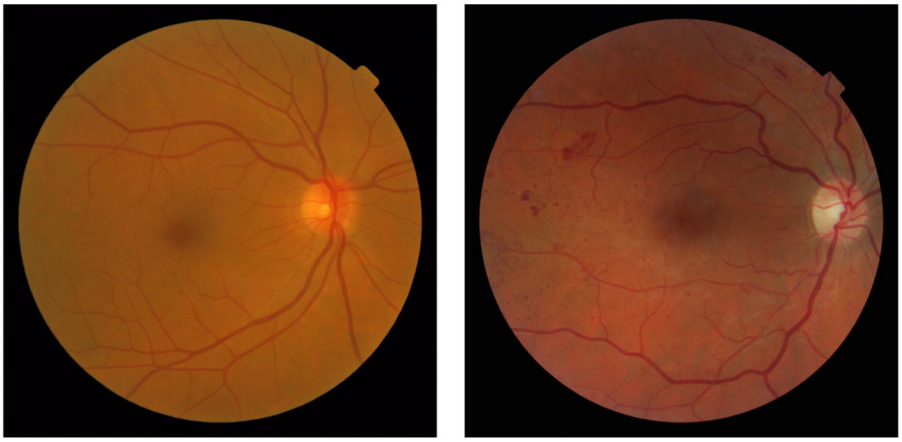

Fig. 1. (a) Healthy retinal image. (b) Retinal image with DR.

and vitreous haemorrhages [10]. Patients presenting PDR require an urgent referral to an ophthalmologist.

New vessels are divided into two categories, new vessels at the optic disc (NVD) and new vessels elsewhere (NVE). They tend to be fine in calibre and are more tortuous and convoluted than normal vessels. Initially they appear as loops or small networks that are located on the optic disc or near a vein. As they grow they form dense lacy networks which usually pass across the underlying veins and arteries [1]. New vessels tend to grow away from the retinal surface and hence can appear out of the focal plane of the photograph, which can result in a blurry and obscure appearance. Examples of new vessels are shown in Fig. 2.

Large scale audits of disease/no disease automated grading systems have shown the benefits they provide [11]. An additional aim is the detection of different stages of DR, which should include the capability of detecting and prioritising PDR images to ensure immediate referral to a specialist. There are many studies investigating the automatic detection of DR focused on microaneurysm and haemorrhage detection [12–16], and exudate detection [17–20]. Conversely, research on the detection of PDR is relatively rare.

New vessel detection methods can be split into two categories, based on whether vessel segmentation is performed or not. Those methods based on vessel segmentation are developed with the purpose of analysing the morphology of the binary vessel map in search of abnormality. The other category is methods based on extracting textural information from the images and therefore avoiding the difficulties that arise from vessel segmentation.

Vessel segmentation has received the largest share of attention in the field of retinal image analysis, studies include [21–28]. A comprehensive review of this mature field of vessel segmentation is provided by Fraz [29]. Studies have shown that vessel calibre relates to hypertension and cardiovascular disease [30]. The main driving force for accurate segmentation has been for the quantification of vessel calibre [31] for cardiovascular studies. Vessel segmentation also forms the backbone for many automated systems aimed at diagnosing ophthalmic disease. However, vessel segmentation techniques struggle to extract new vessels due to their fine calibre and irregular appearance. Also most techniques do not put enough emphasis on removing false responses due to artefacts and other lesions.

The following vessel segmentation techniques were designed with PDR taken into consideration. Ramlugun [32] described a small vessel extraction technique, the main contribution was the varying of the clip limit for contrast limited adaptive histogram equalization (CLAHE) to allow more contrast for small vessels. Zhang [33] applied the matched filter with the first-order derivative of the Gaussian. The main emphasis was not on the increased segmentation of new vessels, but instead the reduction of the false response to exudates which can cause large local densities on the segmented map and therefore can be mistaken for new vessels. Zhang [34] proposed a modified matched filter that used double sided thresholding to reduce the false response to exudates. Fig. 3 shows an example of exudates, also known as bright lesions. Akram [35] proposed the use of the Gabor wavelet for vessel enhancement followed by a multilayered thresholding technique.

The following new vessel detection methods are categorised as those performing vessel segmentation prior to the described analysis methods. Hassan [36] proposed a region based technique where the number of vessels and the area of vessels within a small scanning sub-window were used to indicate new vessels. Welikala [37] also produced a region based technique using five local morphology features. Also included was the prior step of straight vessel removal in order to remove the majority of normal vasculature and therefore simplifying new vessel detection. A comprehensive set of 15 features was developed by Goatman [38] including the number of vessel segments, the mean vessel wall gradient and various tortuosity measures in order to detect NVD. Jelinek [39] used data obtained from the application of the derivatives of Gaussian wavelets to the vessel skeleton to extract morphological based features. Daxer [40] described the retinal vasculature as a fractal and used the fractal dimension to quantify its complexity to indicate the presence of new vessel growth. Karperien [41] furthered this with the analysis of local dimensions using the local connected fractal dimension. Akram [42] proposed a multivariate m-Mediods based classifier with a ten dimensional feature set based on morphological, intensity and gradient based values. Saranya [43] created a feature vector that involved the use of Hu moments for the detection of new vessels. Oloumi [44] proposed the use of modelling the major temporal arcade for the diagnosis of proliferative diabetic retinopathy.

The methods described next are categorised as not performing vessel segmentation and therefore avoid their associated difficulties. Frame [45] applied statistical texture measures, calculated using the grey level co-occurrence matrix (GLCM), to identify irregular distributions of pixel intensities associated with neovascularisation. Acharya [46] calculated texture features from the run length matrix, as well as the GLCM to identify the stage of DR. Multi-scale amplitude modulation frequency modulation (AM-FM) methods were utilised by Agurto [47] for spectral texture analysis to characterise different retinal structures, including new