Detection of Exudates in Retinal Images based on Computational Intelligence Approach

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Abstract-
Currently, there is an increasing interest for setting up medical systems that can screen a large number of people for sight threatening diseases, such as diabetic retinopathy. This automated identification of exudates pathologies in retinal images based on computational-intelligence approach are used to find the diabetics. In which the color retinal images are segmented using fuzzy c means clustering algorithm which following some pre processing step and that segmented regions are divided into exudates and non exudates. The selected feature vectors are then classified using a multilayer neural network classifier to determine whether the image is abnormal/normal.

Index-term
Fuzzy c-means (FCMs), Gabor filters, neural networks, retinal exudates, thresolding.

I.INTRODUCTION

Diabetic retinopathy (DR) is one of the most serious complications of diabetes and a major cause of visual morbidity. It is a progressive disease classified according to the presence of various clinical abnormalities. DR is the most common cause of blindness in people aged 30–69 years [1]. One-fifth of patients with newly discovered type II diabetes have retinopathy at the time of diagnosis. In type I diabetes, vision threatening retinopathy almost never occurs in the first five years after diagnosis or before puberty.

After 15 years, however, almost all patients with type I and two-thirds of those with type II diabetes have background retinopathy [1-2]. Exudates are associated with patches of vascular damage with leakage and typically manifested as spatially random yellow-white patches of varying sizes and shapes. Here, we have concentrated on detecting exudates as the prime marker of DR disease because exudates are directly related to retinal edema and visual loss, and they are the single most important retinal lesion detectable in retinal images. On the other hand, detecting retinal exudates in a large number of images that are generated by screening programmes and need to be repeated at least annually is very expensive in professional time and open to human error[5]. With this motivation in mind, we have developed an efficient system to automate the preliminary analysis and diagnosis of disease. This system combines computational intelligence and pattern recognition with machine learning techniques to analyze diabetic retinal images[3]. Through this system, the abnormal retinal images are automatically discriminated from normal images, and an accurate assessment of retinopathy severity is obtained at pixellevel

II. RELATED WORKS

In segmentation technique are applied to the lesion-based criterion, each single exudate lesion is regarded as an individual connected region, where this region can comprise one or more pixels. Each abnormal retinal image can be segmented into a number of exudate regions[4]. Then, the lesion-based accuracy can be measured in terms of lesions sensitivity and specificity by comparing the obtained results against ophthalmologist's outline of the exudates. However, it is not the number of exudates that is important for the diagnosis. If an algorithm can find all exudates[6], but not the borders in a correct manner, it shows good statistics but poor performance. In fact, the lesion-based accuracy can be assessed either in a pixel-level (pixel resolution) basis or alternatively using a larger collection of pixels, e.g., 10 × 10 patches (patch resolution). Although creating an accurate pixel-based ground truth is not an easy task, but a pixel resolution measure will be more precise than the patch resolution counterpart. In fact, a patch may only be partially covered by exudate pixels.

In the Global and local thresholding technique values were used to segment exudate lesions.Before thresholding, the images were preprocessed to eliminate photographic nonuniformities, and the contrast of the exudates was then enhanced[7]. The drawback of this method was that other bright lesions (such as cotton wool spots) could be identified mistakenly.

In recursive region growing technique using selected threshold values in gray-level images[10]. It was supposed that the processed retinal images are only including exudates, and other bright lesions were not considered. The author reported a lesion-based accuracy of 88.5% sensitivity and 99.7% specificity for the detection of exudates against a small dataset comprising 21 abnormal and 9 normal retinal images. However, these performances were measured based on 10×10 patches. But there is no pixel level resolution.

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3. PRELIMINARY PROCESSING

1. Preprocessing stage

Typically, there is wide variation in the color of fundus from different patients that is strongly correlated to the person's race and iris color. Therefore, we put our data through two preprocessing steps before commencing the detection of exudates. The first step is to normalize the color of the retinal images across the dataset.

We selected a retinal image as a reference, and then applied histogram specification [15] to modify the values of each image in the database [for example, Fig. 1(a)] such that its frequency histogram matched the reference image distribution. Fig. 1(b) shows the result of this normalization

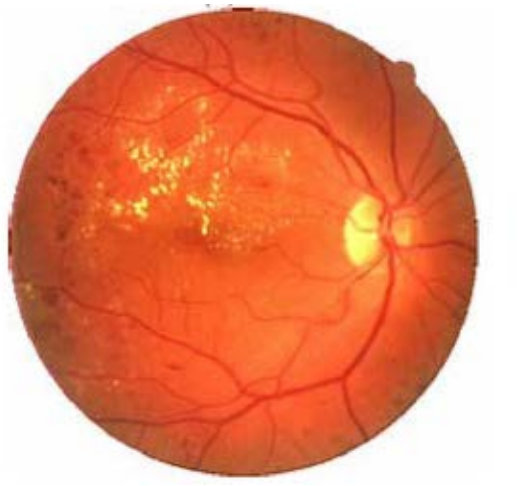

Fig1a) color normalized image

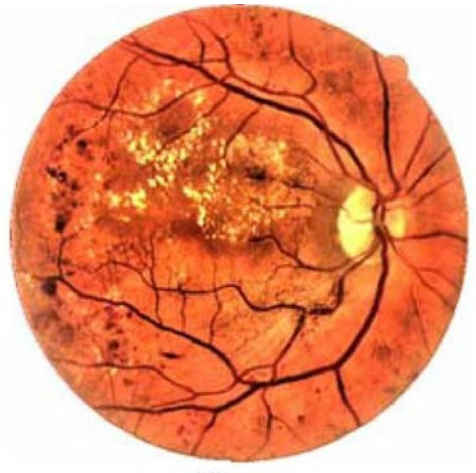

Fig 1b) Contrast enhancement image

The histogram specification technique was independently applied to each individual RGB channel to match the shapes of three specific histograms of the reference image[12]. Consequently, in the second preprocessing step, the contrast between the exudates and the retinal background was enhanced to facilitate later segmentation. While the contrast enhancement improves the contrast of exudates lesions, it may also enhance the contrast of some nonexudate background pixels (e.g., noise), so that these pixels can wrongly be identified as exudate lesions. Here, prior to contrast enhancement, a 3×3 median filter was applied to suppress the noise[13].

2. Retinal Image Segmentation Based on FCMs

A fuzzy approach provides a mechanism to represent and manipulate uncertainty and ambiguity, and allow pixels to belong to multiple classes with varying degrees of membership. we segment retinal images using a two-stage color segmentation algorithm based on Gaussian-smoothed histogram analysis and FCMs clustering [16].

Luv [18] color space the most appropriate space for our segmentation.

a*) Retinal Image Coarse Segmentation:*

At the coarse stage, the segmentation algorithm utilizes the histogram information of the three 1 D color components to estimate the number of valid classes by a statistical evaluation of the histograms. Suppose the signal (histogram) f and a smoothing kernel $g(x,\sigma)$, then the smoothed signal at the scale σ can be written as

$$F(x,\sigma) = f(x) * g(x,\sigma)$$

Where * denotes convolution.F defines a surface in the(x, σ) plane,which is slept out as the Gaussian standard deviation is varied.Having smoothed the image's histograms based on a Gaussian smoothing, the coarse stage begins to segment the image using the located thresholds. The histogram valley locations can be possible solutions for the thresholds. The valleys are obtained by computing the first and second derivative of each 1-D histogram.The histogram peaks represent the number of clusters, and are localized.Each of these clusters is separated from its neighbours by a secure-zone parameter.

Therefore, the number of valid clusters and their corresponding mean vectors that are then utilized in the fine stage can be obtained. These pixels, which are not assigned to any valid clusters, are entered into ambiguous regions, and their fine segmentation is achieved within FCM clustering.

b) Fine Segmentation Based on FCM Clustering:

In the fine stage, FCM assigns any remaining unclassified pixels (pixels from ambiguous regions) to the closest cluster based on a weighted similarity measure between

the pixels in the image and each of *C* (e.g., exudates and nonexudates) cluster centers.Local extrema of this objective function are indicative of an optimal clustering of the image. The function is defined as

$$J_{FCM}(U,v;X)=\sum_{k=1}^{n}\sum_{i=1}^{C}(\mu_{ik})^{m}\left\|x_k-v_i\right\|^2;1\leq m<\alpha$$

where μik is the fuzzy membership value of a pixel k to class i and $X = x1, \ldots, xn$ is a finite sdataset where μik is the fuzzy membership value of a pixel k to class i and $X = x1, \ldots, xn$ is a finite dataset. As most pixels are classified in the coarse stage, a significant computation time required for FCM is saved.

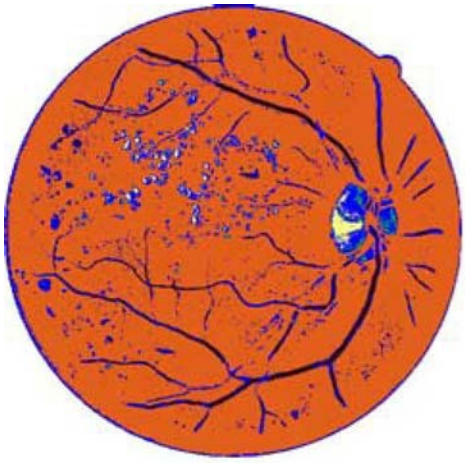

Fig 2a) coarse segmentation result

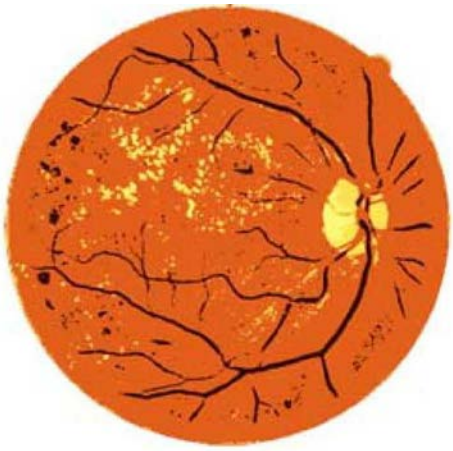

Fig 2 b) Fine segmentation result

3) Feature Selection:

Once our color retinal images are segmented, each image is represented by its corresponding segmented regions[22]. These regions however, need to be identified in terms of exudates and nonexudates[17].Similarly colored objects like exudates and cottonwool spots are differentiated with further features, such as size, edge strength, and texture.

Gabor filters are powerful tools that have been widely used as a model of texture for image interpretation tasks[23]. Mathematically, a 2-D Gabor function g is the product of a 2-D Gaussian and a complex exponential function. Here, to encode appearance of FCM-based segmented regions in terms of texture, and thus discriminate more accurately the exudate regions from other nonexudates, a Gabor filter bank is used[25]. This bank contains 108 filters, 12 orientations (θ spanning from 0◦ up to 180◦ at steps of 15◦), three wavelengths (γ = 1.5, 2.5, 3.5), and three scales (σ = 3, 5, 7).

4) Neural Network:

The multilayer perceptrons NN with three layers has a input layer corresponding to the feature vector. And the hidden layers to find the optimum architecture where all networks are trained using back propagation learning method[26]. A single output node gives the final classification probability, and the sigmoid activation functions are used in the hidden and output layers[8-9].

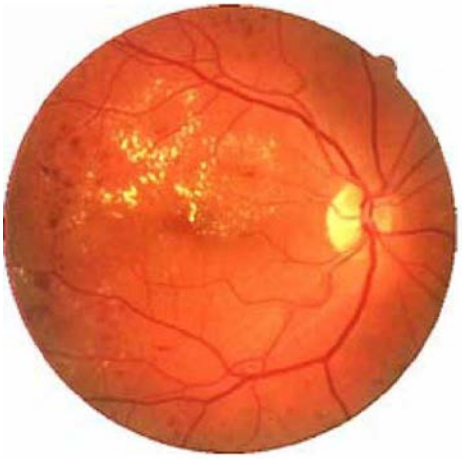

Fig 4a) typical abnormal retinal image.

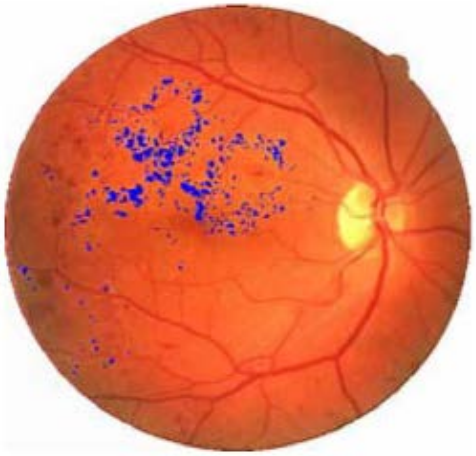

Fig 4b) NN-based identified exudates.

4. CONCLUSION

Past works on exudates identification mainly relied on gray-level information, and were not evaluated on large datasets or failed to give good results for large numbers of images as encountered in a screening process.Moreover, the majority of these methods were assessed only in terms of either lesion-based or image-based criterion. Indeed, the reported lesion-based accuracies were often based on 10×10 or 20×20 patches (patch resolution) ,and no pixel resolution validation. There were clearly certain errors in reported patch resolution accuracies due to the small areas, which some exudates could occupy. However, in medical decision support systems this method achieved, an accurate diagnostic accuracy
assessment in terms of both pixel resolution and image-based resolution.
In future analyze the accuracy of detection of exudates level be increased by using another efficient learning algorithm to the neural network.

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