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Detection of Exudates of Retinal Images Using Neural Network Clustering Method

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Abstract: In recent years, Diabetic retinopathy is one of the major diseases that are caused by damaging of the retinal blood vessels due to long term diabetes. It is important to automatically detect the DR lesions at early stage in order to prevent the further vision loss. Exudates are bright lesions that are considered as primary sign of this disease**.** Most of the existing system proposed to detect the DR. but does not achieve high accuracy and true positive level. To solve this problem the proposed system introduced a new method for the detection of exudates in retinal images. In this system retinal image is preprocessed by using median filter. Then Saturation, Standard deviation, exudates edges are extracted from retinal images. The optic disk is detected by using circular Hough transform method. The hybrid automatic approach is introduced for the extraction of retinal image vessels. The method consists in the application of mathematical morphology and a fuzzy clustering algorithm followed by a purification procedure. In mathematical morphology, the retinal image is smoothed and strengthened so that the blood vessels are enhanced and the background information is suppressed. The fuzzy clustering algorithm is then employed to the previous enhanced image. After that a purification procedure is used to reduce the weak edges and noise and the final results of the blood vessels are consequently achieved. Finally exudates are detected effectively by using neural clustering algorithm. The experimental results show that the proposed system achieves better performance compared with existing system in terms of accuracy, specificity, sensitivity.

Key words: Blood clustering · Diabetic retinopathy · Fuzzy vessels

INTRODUCTION

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. Diabetic retinopathy (DR), the major cause of poor vision, is an eye disease that is associated with longstanding diabetes. If the disease is detected in its early stages, treatment can slow down the progression of DR [1]. The long term diabetes leads to high level of blood sugar that causes damage by altering the blood flow in retinal blood vessels. It is common that in the early stage, diabetic retinopathy shows no symptoms and hence without undergoing medical examination it is not possible to detect the presence of disease [2]. Exudative retinopathy is a condition defined by the presence of white or yellow mass that occurs due to leakage of fats and proteins along with water from blood vessels in the retina [3]. It is essential to detect the presence of exudates in the fundus oculi because accumulation of these exudates may lead to complete blindness. There are so many methods in literature that are used to detect the presence of exudates in the fundus images. Broadly the automatic detection methods are divided into three categories: - (i) thresholding methods, (ii) morphological approach and (iii) artificial neural network approach [4-6]. Franklin *et al*. [7] converted from the RGB to Lab color space. The luminosity layer is replaced with the processed data and then converts the image back to the RGB color space. Contrast enhancement has been done using CLAHE. Features like color, size, shape, edge strength and texture were used with three layers feed forward neural network to classify candidate regions into exudates and non exudates. The method is evaluated using DIARETDB1 database, a mean sensitivity of 96.3%, mean specificity of 99.8% and predictive value of 93.7% have been achieved. Zhang *et al*. [8] detected exudates through three stages; preprocessing, exudates candidates detection and finally classification. Removing of all dark structures and bright artifacts were done in the preprocessing stage, morphological top hat was used to detect small exudates candidates from green channel of

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fundus image. Large exudates candidates were extracted by applying mean filter followed by reconstruction. Classification was done using intensity features and geometric features followed by machine learning technique. The method is evaluated using DIARETDB1_V2, MESSIDOR and HEI-MED, with corresponding area under curve (AUC) of 0.95, 0.93 and 0.94 respectively.Sophark in the paper "Automatic exudates detection from non-dilated diabetic retinopathy retinal images using fuzzy c-means clustering" have proposed FCM clustering method to detect exudates. As an initial step, contrast enhancement is used followed by providing information obtained from image features to a coarse segmentation routine using FCM clustering method. The image features include intensity, standard deviation on intensity, hue and the number of pixels. The optic disc is identified using entropy feature. An FCM clustering algorithm is applied to segmentation along with morphological reconstruction to obtain better segmentation results. The difference image is thresholded and reconstructed to obtain the last result [9]. Hussain *et al.* [10] reported an automated method for detection of, hard as well as soft exudates, using a split and merge technique. This method is based on coarse to fine segmentation principle. In this algorithm, the green channel is used for pre-processing and elimination of optic disc. Coarse exudates detection is based on local variation operator whereas adaptive thresholding technique is used for fine exudates detection. This combination of fine and coarse exudates is used for the improvements in the results. This method provides the performance measure as 89.7% sensitivity and 99.3% specificity.Many more approaches have been used for the automatic detection of exudates but their results have not satisfied the limits of sensitivity, specificity and accuracy.

Proposed Methodology: The proposed system presents an automated method for detection of exudates in retinal images. New methods are developed to localize and isolate the optic disk and detect the exudates.

Fundus images often show luminosity variation, differences in contrast and noise. Pre-processing is a mandatory step to overcome these problems. The median filter is a type of filters that is used to remove noise. Median filter is a non-linear filter which computes median of the pixel set that falls within the filter mask. Each pixel is addressed and it is replaced by the statistical median of its NxM neighborhood. Since the median value is calculated from the neighborhood pixel, it is more robust to outliers and does not create a new realistic pixel value, which preserves edge blurring and loss of image detail. It preserves the sharp high frequency details. The effect of median filter in removing noise is increased as the window size increase. The formula of median filter is

$$\hat{F}(\mathrm{x},\mathrm{y}) = \underset{(s,t)\in S_{xy}}{mediam}\{g(\mathrm{s},\mathrm{t})\}$$

where,

$\hat{F}(\mathrm{x},\mathrm{y})$ - Filter response at a given coordinate
S_{xy} - m×n sub-image of the input image
x, y - Coordinates in the input image.

After reduce of noises from the retinal images, the image is enhanced for efficient segmentation purpose.

Feature Extraction: Feature of the retinal images are extracted for finalizing the exudates. Here Saturation, Standard deviation, I_{CLAHE} and exudates edges are extracted from retinal image

Green Plane Extraction: Retinal fundus images are color images. It consists of three channels red, green and blue. It is observed that the red and blue channels do not have significant information for exudates detection and thus it is sufficient to use the green channel only. The green plane was used in this system due to the greater distribution of intensity through the image. While the green component of the color retina image gives the best result in the contrast of blood vessels (darker blood vessels on a bright background). Therefore, the green channel of the image is used in the automated analysis of fundus images.

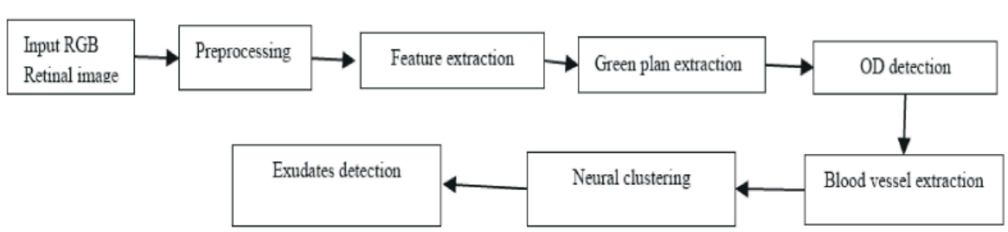

Fig. 1: Flow diagram for proposed system: Input Image with Preprocessing

Optic Disk Detection: Optic disc detection is one of the main task in detection of exudates. Because optic disc has similar characteristics of exudates such as brightness, color and contrast. Normally optic disc similar to circular structure. So we use the circular Hough transform method to detect optic disc. The Hough transform are used to detect the shape of object in image. Circular transform are implemented here which is used to find the optic disc in the fundus image. The basic idea behind the Hough transform is to transform the image into a parameter space that is constructed specifically to describe the desired shape analytically. Maxima in this parameter space then correspond to the presence of the desired shape in image space. The circular Hough transform is almost identical to the Hough transform for lines, but uses the parametric form for a circle as denoted in equation (1),

$$(x-a)^2 + (y-b)^2 + r^2 = 0,$$

where (a, b) is the centre of the circle of radius r that passes through (x, y). The Hough space is three dimensional (3D). The gradient image is transformed to a set of three parameters, representing the accumulator, its center and its radius. For each feature point, votes are accumulated in an accumulator array for all parameter combinations. The accumulator will have set of edge points; each edge points contribute a circle of radius r in the accumulation space. The accumulation space has a peak where these contributory circles overlap at the centre of the original circle. The centre is an N×2 matrix with each row containing the (x, y) positions of the circles detected in the image. The estimated radius of the circles detected is stored in an N×1 column vector with a one-to-one correspondence to the center array. The corresponding circle can then be plotted over the original fundus image

Fuzzy Clustering for Vessel Extraction: A hybrid automatic approach is introduced for extracting vessels from retinal image. The method consists in the application of mathematical morphology and a fuzzy clustering algorithm followed by a purification procedure. In mathematical morphology, the retinal image is smoothed and strengthened so that the blood vessels are enhanced and the background information is suppressed.

To satisfy the need of extracting larger vessels, the length of structuring elements is selected to be close to the diameter value of the largest vessels. Structuring elements are applied here to perform an opening operation γLi on the original image S0. This opening operation consists of two steps. The first step is to erode the image defined as γL and the second step is to dilate the image defined as δL. The maximum response of 12 directions is defined as the opened image S. The reconstructed image Sop that is the smoothed image obtained by carrying out an opening by reconstruction γrec S0 to the original image S0 and the opened image S. The calculation process is defined as follows:

$$\gamma L = \delta L\left(\varepsilon_L(M)\right)$$

$$S = \underset{i=1.....12}{MAX}\left\{\gamma Li(s_0)\right\}$$

After the image has been smoothed, the Top-Hat trans- form is applied to strengthen the vessels in the image by choosing appropriate structuring elements. Here, the TopHat transform is applied to the smoothed image at 12 directions and the computational results of the 12 directions are summed up to increase the gray difference between the vessels and the background. The corresponding formula is as follows:

$$S_{sum} = \sum_{i=1}^{12}(S_{op} - \gamma_{Li}(s_0))$$

The opening by reconstruction γrec Slap and the closing by reconstruction φrec S1 are respectively defined as

$$S_1 = \gamma_{slap}^{rec}(\underset{i=1....12}{max}\{\gamma_{Li}(Slap)\})$$

And

$$S_2 = \varphi_{s1}^{rec}(\underset{i=1,....12}{min}\{\varphi_{Li}(S1)\})$$

Here

$$\varphi_{s1}^{rec} = N_{max} - \gamma_{(Nmax\text{-}s1)}^{rec}(N_{max} - s)$$

$$\varphi_L(s) = \varepsilon_L(\delta_L(S))$$

where Nmax is the maximum gray level of the original image and φL is the gray closing operation. Equations (10) and (11) are applied to the previous smoothed image, the proposed system can get a smoothed image.

When the retinal vessels have been enhanced, the next step is to extract the vessels from the image. Here, we apply the most popular fuzzy clustering method, i.e., the fuzzy cmeans (FCM) clustering algorithm to extract the vessels.

The algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted-withingroup sum of squared errors J_{FCM}.

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q \; d^2(x_k v_i)$$

where X = {x1, x2,...,xn} $\subseteq R^p$ is the data set in the pdimensional vector space, n is the number of data items, c is the number of clusters with 2 $\leq$ c u_{ik} is the degree of membership of x_k to the i-th cluster, q is a weighting exponent on each fuzzy membership, v_i is the prototype of the centre of cluster i, $d^2(x_k, v_i)$ is a distance measure between object x_k and cluster centre v_i. A minimum of the objective function JFCM can be obtained via an iterative process, which is as follows.

Step 1: Set values of c, q and γ.

Step 2: Initialize the fuzzy partition matrix $U = [u_{ik}]$.

Step 3: Set the loop counter b = 0.

Step 4: Calculate the c cluster centers $\{v_i^{(b)}\}$ with $U^{(b)}$

$$v_i^{(b)} = \frac{\sum_{k=1}^{n} (u(b)_{ik})^q x_k}{\sum_{k=1}^{n} (u(b)_{ik})}$$

Step 5: Calculate the membership $U^{(b+1)}$. For k = 1 to n, calculate the following:

$I_k = \{i \mid 1 \leq i \leq c, d_{ik} = \|x_k - v_i\| = 0\}$,
$\tilde{I} = \{1, 2,...,c\} - I_k$.

For the k-th column of the matrix, compute new membership values: If $I_k = \varphi$, then

$$u^{(b+1)} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(q-1)}}$$

Step. 6: If $\|U^{(b)} - U^{(b-1)}\| < \gamma$, stop. Otherwise, set b = b + 1 and go to Step 4.

When the algorithm has converged, a defuzzification process takes place in order to convert the fuzzy partition matrix U to a crisp partition. A number of methods have been developed to defuzzify the partition matrix U, among which the maximum membership procedure is most important. The procedure assigns object k to class C with the highest membership: $C_k = \arg\{\max_i (u_{ik})\}$, i = 1, 2,. . . , c. (17)

With this procedure, the fuzzy image is then converted to a crisp one. The result and the final extraction or segmentation result is achieved in this case.

Neural Network – Based Clustering: Neural network – based clustering is used to detect the Exudates by using extracted features. Neural networks have solved a wide range of problems and have good learning capabilities. Their strengths include adaptation, ease of implementation, parallelization, speed and flexibility. Neural network – based clustering is closely related to the concept of competitive learning.

For a given set of m-dimensional points $\{x_i\}i^N \in R^m$ we calculate a quadratic (N × N) -matrix of Euclidean distances between them: $D = (D_{ij})_{i,j=1}^{N}$. In what follows we need these distances D_{ij} only. We suppose that in each point xi there is a neuron with initial activity $S_i(0)$, which will be defined below

1) For a fixed interaction threshold T > 0 let us set the value of a connection w_{ij} between ith and jth neurons as

$$| \, Wij = \begin{cases} \dfrac{T^2}{D_{IJ}^2 + T^2} & when \;\; D_{ij} \leq T \\ 0 & when \;\; D_{ij} > T \end{cases}$$

As we see, there are no connections between neurons, if the distance between points is greater than T. Note, ( ) 1 w_{ii} (T)$\equiv \forall$ i.

2) Let us set initial activity of each neuron to be

$$S_I(0) = \sum_{j=1}^{N} w_{ij} \geq 1$$

Neurons, which are inside agglomerations of the points, have large initial activity, because they have more nonzero connections than neurons at the periphery of agglomerations.

3) We start the activities "transmitting" process:

$$S_i(t+1) = S_i(t) + \alpha \sum_{j=1}^{N} w_{ij} (S_i(t) - S_j(t))$$

where α is the parameter characterizing the transmitting speed. It is easy to see that during the transmitting process a neuron with large initial activity "takes away" activities from neurons with whom it interacts and whose activities are less. The activities of these surrounding neurons decrease steadily.

4) If during the transmitting process the activity of a neuron becomes negative $S_i(t) < 0<$, we set $S_i(0)$ and eliminate this neuron from the transmitting process

(it has nothing to give away). drop out giving away their activities to neurons inside the agglomerations. This means that step by step the neurons from the periphery will leave the field. Gradually, we shall have a situation, when only some far from each other non-interacting neurons with nonzero activities remain. Subsequent transmitting is impossible and the procedure stops.

5) Suppose as a result of the transmitting process K neurons remain far away from each other. The input points x_i corresponding to these neurons will be called the centers of the classes. All other input points x_j are distributed between classes basing on the criterion of maximal closeness to one or another center. The items 1)-5) are carried out for a fixed interaction threshold T. It is clear that if $T \approx 0$, no one neuron interacts with another one. All the neurons have the same activities $S_i(0)= w_{ii} = 1$. No transmitting process will have place. So we get a great number N of classes, each of which consists of one input point only. On the other hand, if the interaction threshold T is very large (for example, it is greater than max (D_{ij}) /2 all neurons are interacting with each other and as the result of transmitting only one neuron remains active. We can say that it is located inside "the cloud" of the input points. In this limiting case there is only one class including all the input points. Finally the exudates are detected effectively from the retina fundus image.

Experimental Results: The results of the various operations in the detection of exudates and other features from the retinal image are explained as follows. The preprocessing operations are performed on the green plane of the image and also on the gray scale image to detect blood vessels, exudates and in the elimination of optic disc. The results obtained after the operations are as follows: The input to the system is shown in Figure 2, which is an RGB image.

The histogram equalized green component of the image after preprocessing the optic disc area shown in Fig. 3. The figure shows that the blood vessel in the optic disc area are preserved. The segmentation is applied on the image and the resulting image contains blood vessel along with noise..The noise need to be eliminated which is done in the further steps. The final blood vessel image after Logical AND operation is shown in Fig 5. For proper detection of exudates regions the optic disc need to be removed. A hough transform is used to find the optic disk and eliminated optic disc as shown in fig

Fig. 2: Input RGB image

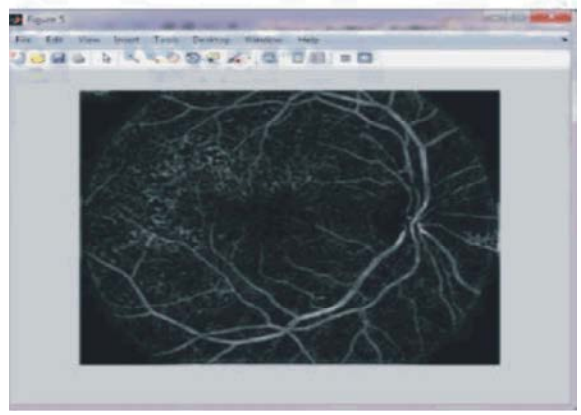

Fig. 3: Preprocessing suppressed image

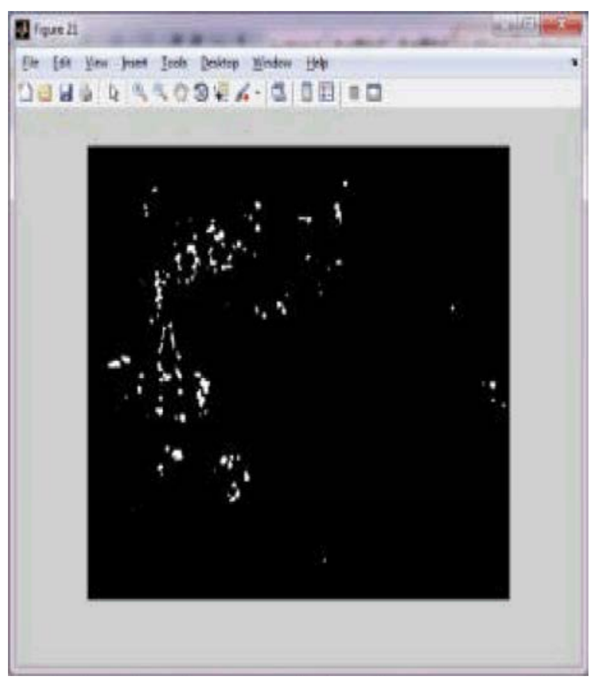

Fig. 4: Blood vessel image

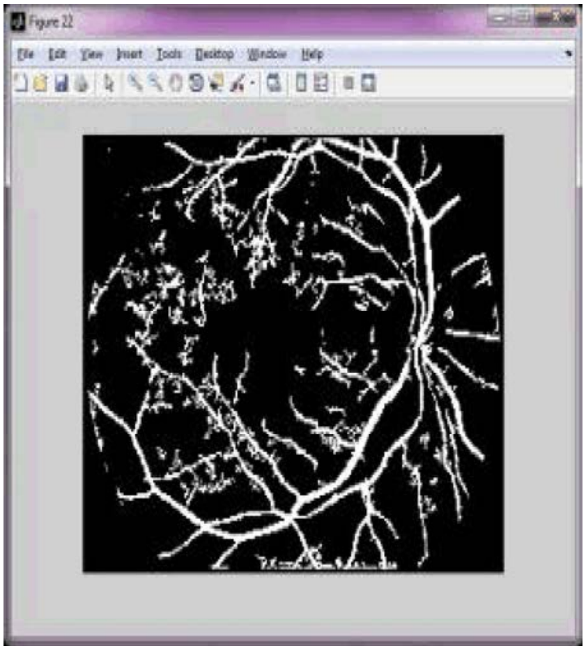

Fig. 5: Final exudates after neural network cluster

CONCLUSION

Early detection and timely treatment of DR can slow down the progression of the disease and avert blindness. Further with limited medical staff, an automated detection system can be used by non experts to indicate which patient requires referral to an ophthalmologist for additional investigation and treatment without further delay. The proposed system efficiently detects the Exudates of Retinal Images Using Neural Network Clustering Method. The experimental results show that the proposed system achieves better performance compared with existing system in terms of accuracy, specificity, sensitivity and F-measure.

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