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RETINAL BLOOD VESSEL SEGMENTSTION AND DETECTION OF DIABETIC RETINOPATHY

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***Abstract*— The appearance and structure of blood vessels in retinal images play an important role in diagnosis of eye diseases especially diabetic retinopathy. Automatic vessel segmentation has a great potential to assist ophthalmologists in the early detection of DR. This study proposes a technique based on morphological image processing and fuzzy logic to detect hard exudates. The exudates are identified by using mathematical morphology that includes elimination of optic disc. The hard exudates are extracted using an adaptive fuzzy logic algorithm that uses values in the RGB colour space of retinal image to form fuzzy sets and membership functions. The fuzzy output for all the pixels in every exudates is calculated for a given input set corresponding to red, green and blue channels of a pixel in an exudates. This fuzzy output is computed for hard exudates.**

***Keywords*— Diabetic Retinopathy, Exudates, Fundus Image, Optic disc, Fuzzy**

I. INTRODUCTION

Diabetic retinopathy refers to a group of eye problems that people with diabetes may face as a complication. If the early stage of retinopathy is detected successfully the ophthalmologist would be able to treat the patient by advanced laser treatment to prevent total blindness. The detection and measurement of blood vessel can be used to classify the severity of disease, as part of the disease of automated diagnosis of disease or in the assessment of the progression of therapy. Retinal blood vessels have measurable changes in diameter, branching angles, length, as a part of a disease. Thus a reliable method of blood vessel extraction and segmentation would be valuable for the early detection and characterization of changes due to such diseases.

Diabetic retinopathy occur when tiny vessels swell and leak fluid, cotton-wool spots, micro aneurysms or haemorrhages. The early stage of DR is referred to as micro aneurysm which appears as tiny, dark red spots or minuscule haemorrhages. The size varies from 10 to 100 μ and it approximate to diameter of an average optic disc. Cotton-wool spots are yellowish white, fluffy lesion in nerve fibre layer are also called soft exudates. These spots are created as a result of swelling of the nerve fibre axons. Although soft exudates are very common in DR. Hard exudates are typically bright, reflective and common in DR. The aim of this research to develop to a system to detect hard exudates in DR. The exudates are identified using morphological methods. The algorithm proposed in this paper detects hard exudates in DR using the principles of mathematical morphology methods and fuzzy logic. At the initial stage, the exudates are identified using mathematical morphology. This stage can be divided into three sub stages, namely pre-processing optic disc elimination and exudates detection.

Salvatelli *et. al.* [2] have analysed and tested several correction techniques. Aim of that was to establish a qualitative assessment of the adequacy of different methods for pre processing stages in a DR diagnosis system. They have obtained good results for the colour model using RGB for image analysis and hue saturation intensity (HSI). They have used morphologically and local enhancement techniques to address nonuniform illumination. The results have been obtained by homomorphic filtering of luminance correction, together with morphological filtering for contrast enhancement. The processing stages were tested using fuzzy C means (FCM) and local Hurst (self correction) coefficient for unsupervised segmentation of the abnormal blood vessels. However, the technique does not seem to address the effect of the optic disc for whether the disc is removed in order to obtain the results.

Iqbal *et. al.* [3] has presented a method to identify DR using digital signal processing and image processing techniques. They have employed colour space conversion, zero padding of image edges, median filtering and histogram equalization with overlap mean for the image pre processing stage.

A method to enhance exudates using fuzzy morphology is proposed in [4] where, a colour fundus image is converted to gray scale image first and followed by a fuzzy morphological closing operation to enhance boundaries of exudates. At the final stage the resulting image is added to the original image to obtain the enhanced image. These enhanced images provide good results for clinical examination. Sopharak *et. al.* [6] have proposed a FCM clustering algorithm for segmentation with subsequent morphological reconstruction to obtain better segmentation results.

II. METHODOLOLGY

A. Systematic overview

The accurate retinal blood vessel segmentation is required for an automatic diagnosis system. The input to the system is a colour fundus image. The algorithm proposed in this paper detects hard exudates in DR using mathematical morphology methods and fuzzy logic. The three main stages for DR detection are pre-processing stage, optic disc elimination and exudates detection as shown in Fig. 1. The main modules of

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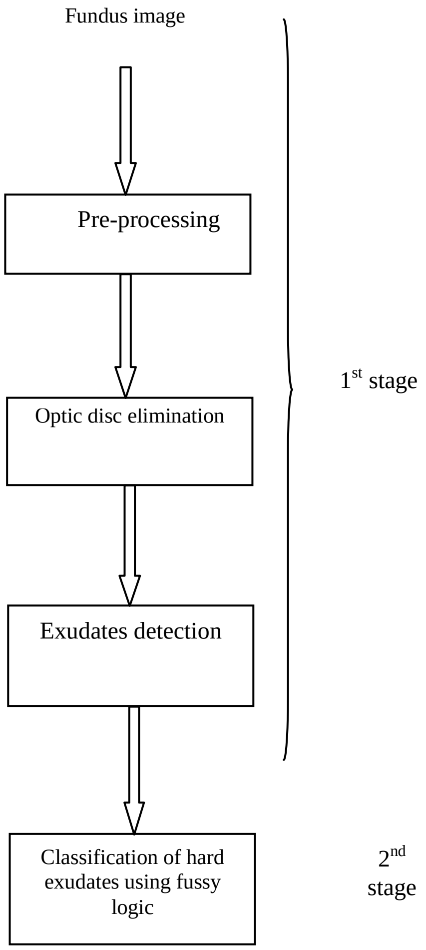
pre-processing stage are RGB to HSI conversion, contrast enhancement, filtering, morphological operations and thresholding.



- RGB to HIS conversion: The RGB colour model is an additive system in which each colour is defined by the amount of red, green and blue light emitted. The HSI definition of saturation is a measure of colours purity or grayness. Purer colours have a saturation value closer to 1, while gray colours have saturation value closer to 0. The HSI intensity is defined by,

$$I = R + G + B/3 \tag{1}$$

- Median filter

  The median filter is applied to the intensity band of the image for noise suppression. This filtering is a nonlinear process useful to reduce impulsive and salt and pepper noise. This filter helps to preserve edges. Median filtering smoothes the image like low pass filter.

- Contrast enhancement

  The contrast limited adaptive histogram equalization was applied for contrast enhancement to prevent over saturation of the homogenous areas in retinal image. CLAHE operates on small components called tiles rather than the entire image. The contrast of each tile is enhanced. Then the whole tiles are combined to get the enhanced image by using bilinear interpolation.

- Gaussian filter

  The Gaussian function is applied for noise suppression. The Gaussian smoothing operator is a 2D convolution operator. It is similar to mean filter but uses a different kernel. The Gaussian distribution in 2-D has the form:

$$G(x,y) = \frac{1}{2\pi\alpha^2} e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)} \tag{2}$$

- Morphological operations

  Morphological closing is used to fill gaps in an image and smooth their outer edges. It is an important operator from the field of mathematical morphology. Closing is similar in some ways to dilation in that it tends to enlarge the boundaries of foreground regions in an image.

B. Optic disc elimination

At first, the closing operator with a flat disc shape structuring element is applied to the pre processed image I_1. The resultant image is binarised using a thresholding technique. The new binary image consists of all the connected regions. Other than the background, the component having the largest number of pixels with circular shape contains the optic disc and therefore extracting this component separates the optic disc from all the other structures in the retinal image. If there is alargest connected component compactness is measured by

$$C(R_i) = 4\pi \frac{A(R_i)}{P^2(R_i)} \tag{3}$$

Where $A(R_i)$ is the number of pixels in ith region and $P(R_i)$ is the number of pixels around R_i. The compactness can be measured by applying two thresholding techniques the P-tile method [16] and Nilblack's method [17, 18] separately. The optic disc considered as the largest connected component that provides high values of compactness among these two methods. In this paper, the optic disc is eliminated before detecting exudates as the optic disc and exudates contain similar colour and intensity. Fig. 3a shows the resultant image after applying morphological closing operator with a flat disc to eliminate high contrast blood vessels. Then, the optic disc could be identified as the largest circular connected component in the fundus image. A weight of 1.3 is used in Nilblack's method for thresholding. The region containing the optic disc is brighter than other regions in the retinal images. The optic disc occupies ~2% of bright regions in fundus images with the rest being the background. This percentage is used to perform the ptile method. Thus obtain the binary images as in Figs. 3b and c. The largest connected component which provides a value of high compactness among these two methods is considered as the optic disc. In this case, as shown in Fig. 3d, the binary

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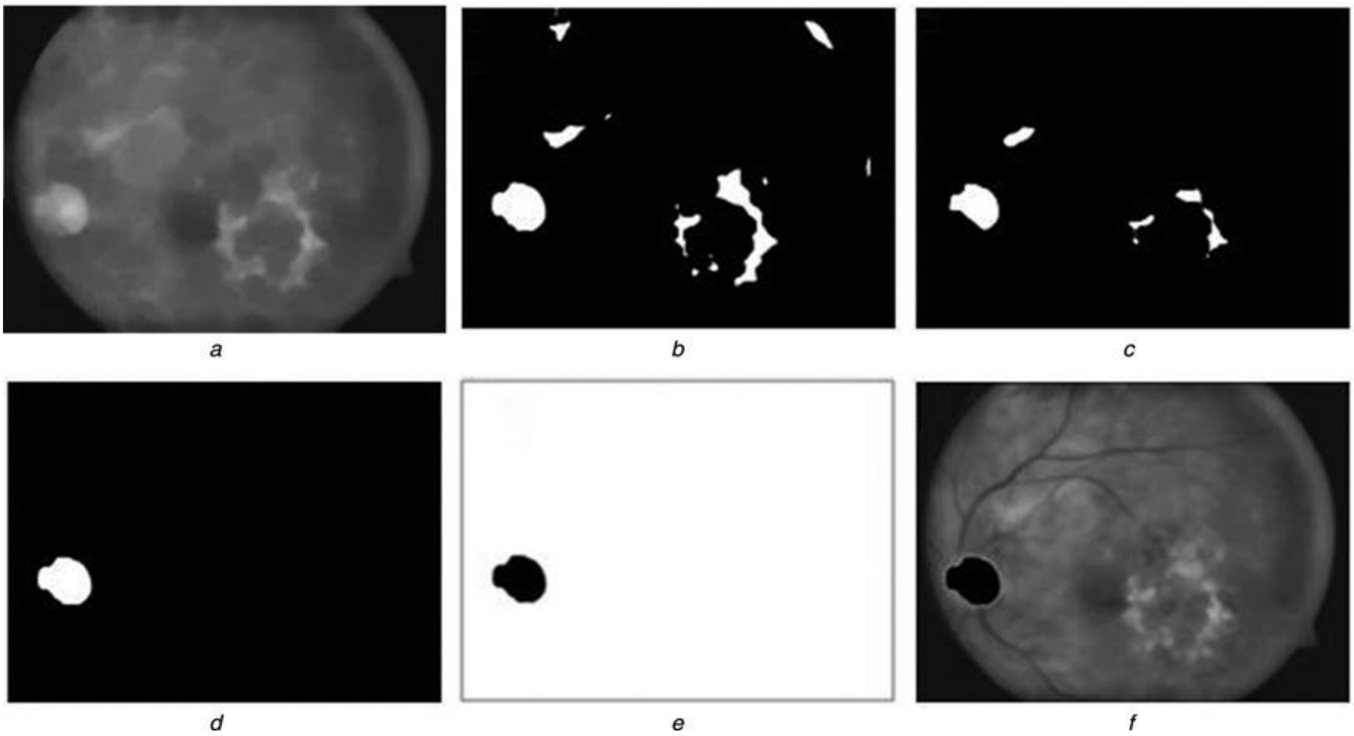

Fig. 3 Output images obtained during elimination of the optic disc
a Applying morphological closing operator
b Thresholded image using Nilblack's method
c Thresholded image using percentile method
d Large circular connected component
e Inverted binary image with large circular component
f Optic disc is eliminated from the pre processed image

image obtained after applying Nilblack's method provides a high compactness for the large circular component.

The Hough transformation can also be used to remove the optic disc of retinal images, the results are not accurate when its shape is not circular [19]. The Hough transform is not a reliable method to detect the optic disc as all retinal images do not have circular optic discs.

C. Exudates Detection

The next step is to identify exudates from the image, from which the optic disc was eliminated. The morphological closing operator with a flat disc shape structuring element is applied to that image to remove blood vessels as both exudates and blood vessels exhibit high contrast (Fig. 4a). Then applied a morphological closing operator with a radius of 16 pixels-flat disc shape structuring element to eliminate the high contrast blood vessels in fundus images before applying the thresholding techniques. It is used to preserve the disc shaped objects in retinal image. Then the standard deviation of the resultant image is calculated.

The triangle method [20] is used for obtaining the thresholded image after enhancing the image i.e., Fig. 4c. This enables to extract every minute bright region with borders of large bright regions. The detection of exudates are confounded by borders of both the optic disc and the image and then subtract the dilated optic disc region, from the thresholded image after removing the image border by applying the morphological closing operator to obtain closely distributed exudates (Fig. 4d). At the next step, flood filling is carried out on all holes (Fig. 4e) to create a marker image.

During the morphological reconstruction (Fig. 4g), the peaks in the marker image dilate until the contour of the marker image fits under the mask image. The difference image between the resulting image of the previous step and the intensity band of the original image is taken for thresholding. The output of the thresholded image, (Fig. 4h) is super-imposed on the original RGB image. Thus we can extract the exudates (Fig. 4i).

D. Classification of hard exudates using fuzzy logic

- Fuzzy sets and membership functions (MFs): If X is a collection of objects denoted generically by x, then a fuzzy set A in X is defined as a set of ordered pairs

  $$A = \{(x, \mu A(x))|x \in X\}$$

  where $\mu A(x)$ is the membership function for the fuzzy set A. The MF maps each element of X to a membership degree between 0 and 1 such that μA: $X \rightarrow [0, 1]$.

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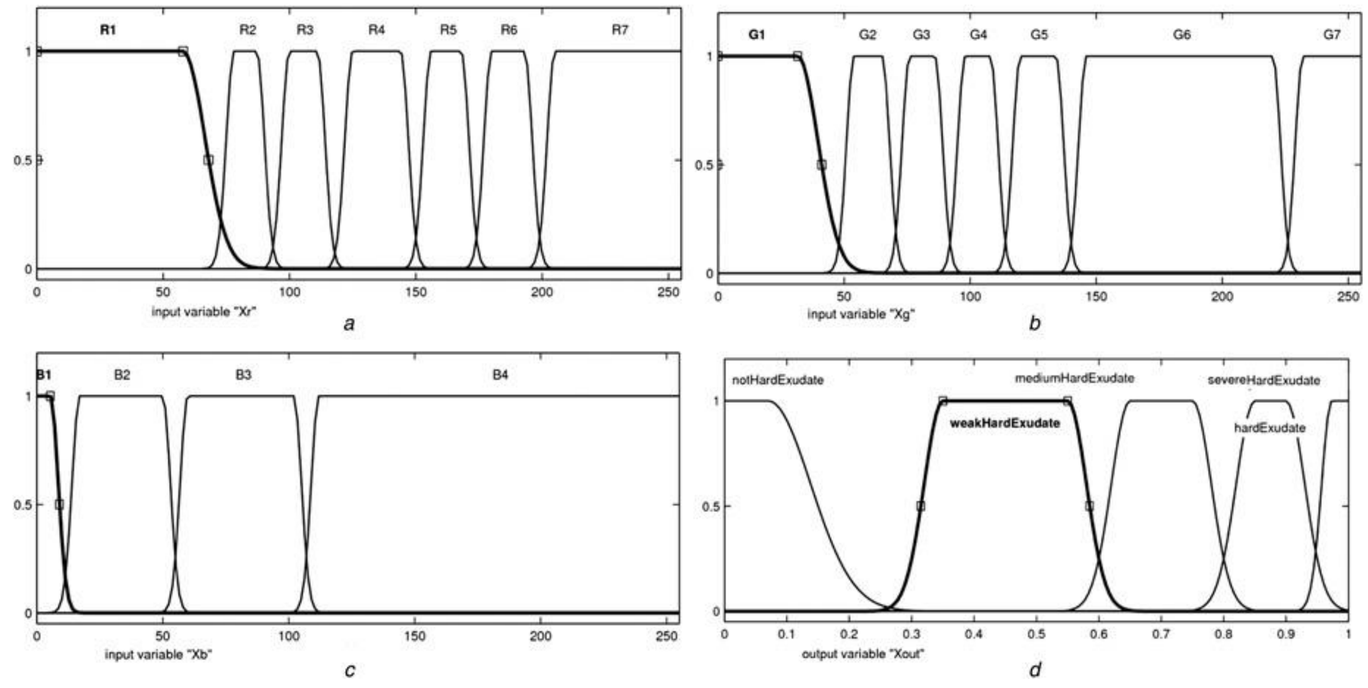

Fig. 5 *MFs of variables*
a x
b xg
c xb
d xou

- Support of a fuzzy set: The support of a fuzzy set A is the set of all points with non-zero membership degree in A
  (A) = {x∈ X|μA(x) > 0}.
- Crisp value: The crisp value x*, which is often referred to as the defuzzified output, is given by

$$I_3(x) = \frac{1}{N-1} \sum_{i \varepsilon W(x)} \left(I_2(i) - \overline{I_3(x)}\right)^2 \qquad (4)$$

The final stage in the proposed technique is to identify the exudates as hard exudates using fuzzy logic. We used values proposed in a research by Nayomi Geethanjali Ranamuka, Ravinda Gayan N. Meegama[1]. The RGB colour space of retinal image to form the fuzzy set and MFs. It uses the red, green and blue values of a pixel as three input values xr, xg and xb for the fuzzy inference system giving a single output. To calculate the output of given xr, xg and xb for a specific rule, the fuzzy inference system provides the degree of membership to the output variable Xout as shown in Fig. 5. A de-fuzzification function as mentioned above, based on the centroid method. It is used to compute the final output for identification of hard exudates. The method presented in this paper determines the fuzzy output for a given input set (xr, xg, xb) corresponding to red, green and blue channels, respectively, of a pixel in an exudate using fuzzy logic. These fuzzy outputs are evaluated for all the pixels in every exudates in the retinal image. A region is considered to be a hard exudates if the average fuzzy value is > 0.25. Subsequently, the fuzzy output is computed for hard exudates according to the proportion of the area of the hard exudates. Given below are the fuzzy rules [1] that we apply to detect hard exudates. In these fuzzy rules, '&' denotes the AND operator.

Fuzzy rules:

if xr [R1|xg [G1|xb [B4 then Xout is notHardExudate
if xr [R2&xg [G2&xb [B1then Xout is weakExudate
if xr [R2&xg _ G2&xb _ B1 then Xout is notHardExudate
if xr [R3&xg [G3&xb [B1 thenXout is weakHardExudate
if xr [R3&xg [G3&xb [B2 thenXout is weakHardExudate
if xr [R3&xg [G3&xb [B3 thenXout is notHardExudate
if xr [R3&xg _ G3Xout is notHardExudate
ifxr[R4&xg[G3&xb[B1thenXoutismediumHardExudate
ifxr[R4&xg[G3&xb[B2thenXoutisweakHardExudate
ifxr[R4&xg_G3XoutisnotHardExudate
if xr [R5&xg [G2 then Xout is notHardExudate
if xr [R5&xg [G3 then Xout is notHardExudate
if xr [R5&xg [G4 then Xout is notHardExudate
if xr [R5&xg [G5&xb [B1 then Xout is HardExudate
if xr [R5&xg [G5&xb [B2 then Xout is HardExudate
if xr [R5&xg [G6 then Xout is notHardExudate
if xr [R5&xg [G7 then Xout is notHardExudate

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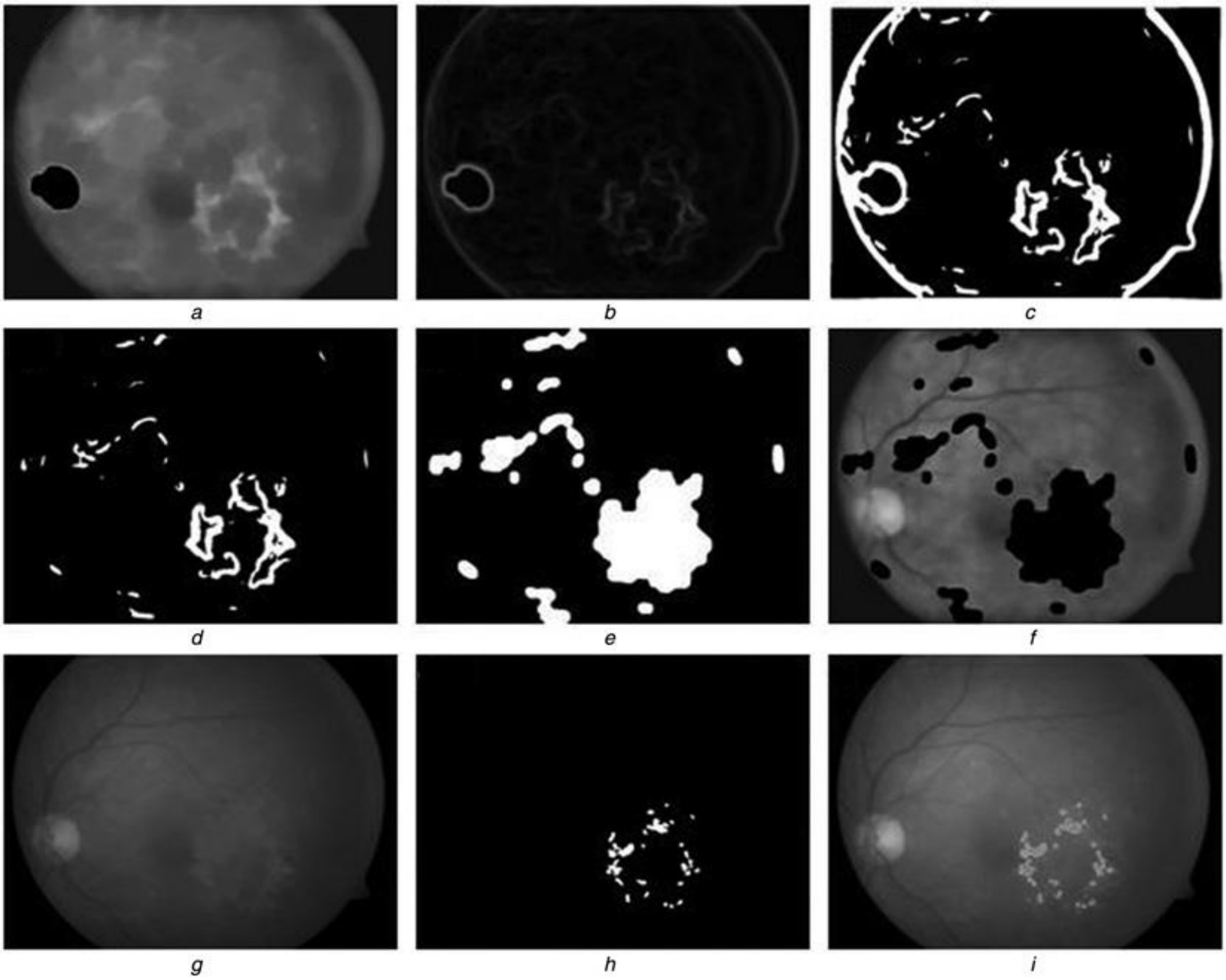

Fig. 4 Output images of exudates detection stage
a Applying morphological closing operator
b Standard deviation of the image
c Thresholded image using triangle method
d Unwanted borders were removed
e Holes are flood filled
f Marker image
g Morphological reconstructed image
h Thresholded image
i Result is super imposed on original image

if xr [R6&xb [B3 then Xout is notHardExudate
if xr [R6&xg [G2 Xout is notHardExudate
if xr [R6&xg [G3 Xout is notHardExudate
if xr [R6&xg [G4&xb [B1 then Xout is HardExudate
if xr [R6&xg [G4&xb [B2 then Xout is HardExudate
if xr [R6&xg [G5&xb [B1 then Xout is HardExudate
if xr [R6&xg [G5&xb [B2 then Xout is HardExudate
if xr [R6&xg [G6&xb [B1 then Xout is HardExudate
if xr [R6&xg [G6&xb [B2 then Xout is HardExudate
if xr [R6&xg [G7 then Xout is notHardExudate
if xr [R7&xb [B3 then Xout is notHardExudate
if xr [R7&xg [G6&xb [B1 thenXout is severeHardExudate
if xr [R7&xg [G6&xb [B2 thenXout is severeHardExudate
if xr [R7&xg [G5&xb [B1 thenXout isnotHardExudate
if xr [R7&xg [G5&xb [B2 thenXout isnotHardExudate
if xr [R7&xg [G2thenXout isnotHardExudate
if xr [R7&xg [G3thenXout isnotHardExudate
if xr [R7&xg [G4thenXout isnotHardExudate

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Table 2 PARAMETERS FOR GAUSSIAN COMBINATION MF OF Xout

Membership function	Value of parameters [σ1c1σ2c2]
notHardExudate	[0.0008493 0 0.06795 0.07]
weakHardExudate	[0.03 0.35 0.03 0.55]
mediumHardExudate	[0.03 0.65 0.03 0.75]
hardExudate	[0.03 0.85 0.03 0.9]
severeHardExudate	[0.0161 0.9733 0.0256 1]

III. RESULTS AND DISCUSSION

We have chosen forty images from the publicly available DR dataset DIARETDB0 and DIARETDB1 [29]. We have selected the images with a size of 1500 × 1152 pixels to test the proposed technique using Matlab version 7.10. The identified exudates are classified as hard exudates using fuzzy classifier. We first classify each exudates as a hard exudates by assigning a crisp value for each hard exudates. By using this crisp value, computed the values for all the exudates according to the proportion of its area. From Fig. 6a we can see the fundus image which has soft exudates and very tiny hard exudates. The algorithm identified the soft exudates. A fundus image with weak hard exudates is shown in Fig. 6b. The algorithm has detected 42% DR hard exudates in this image. Strong hard exudates are represented in Fig. 5c with 89% hard exudates. The crisp logic is created according to the MF of linguistic variables of Xout. Using this logic, an exudate is at least a weak hard exudate if the output crisp value of an exudate becomes > 0.25. We found the fuzzy output less than but very close to 0.25 for very tiny hard exudates. Both the tiny hard exudates and soft exudates exhibit similar colour intensities. It makes extremely difficult to separate both these types of exudates. As a result, at certain times, the technique identifies these very tiny hard exudates as non-hard exudates.

In this research, we tried to obtain better results for overlapping Gaussian combination MFs as shown in Fig. 5. We have checked the fuzzy output values for different degrees of overlap between the MFs and it provided some inaccurate results for low degrees of overlap between the MFs. The fuzzy output values of very tiny hard exudates have decreased than the expected fuzzy output values. Such low degrees of overlapping MFs with tiny hard exudates being identified as non-hard exudates. The fuzzy output values of non-hard exudates (except soft exudates) have increased whereas the fuzzy output values of weak hard exudates have decreased for low degrees of overlap between the MFs. Therefore such non-overlapping MFs may produce inaccurate results confirming the importance of having overlapping MFs for detection of hard exudates. Although good accuracy and specificity rates were achieved by using proposed algorithm. Hemorrhages detection could be also added to the system in order to increase its ability to verify the degree of diabetic retinopathy.

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