A Fuzzy-based Image Segmentation on Diabetic Retinopathy Model

Sherin M. Youssef [a], Laurine A. Ashame [b]
Computer Engineering Department, college of Engineering and Technology, Arab Academy for Science, technology and Maritime Transport, Abu Qir, Alexandria, Egypt, P.O.: 1029
[a]sherin@aast.edu, [b] laurinearmeya1@gmail.com

Salema F. Fayed [c]
Computer Engineering Department, college of Engineering and Technology, Arab Academy for Science, technology and Maritime Transport, Abu Qir, Alexandria, Egypt, P.O.: 1029
[c] salema.fayed@gmail.com

***Abstract*—Clinical reports done suggested that more than ten percent patients with diabetes have a high risk of eye issues. The retinal fundus images are commonly used for detection and analysis in diabetic retinopathy disease. This work presents several state to extract the anatomic components and lesions in colored fundus photographs and some decision support methods to help early clinical diagnosis detection. It also introduces a model of detection in fundus images by automated segmentation of region of interest (ROI). Automatic segmentation of retinal blood vessels from retinal images is applied to make landmarks detection more efficient. The proposed model integrates adaptive Otsu's Threshold and Segmentation using FUZZY C-MEANS clustering for automated detection of hard yellow spots. The proposed hybrid fuzzy-based ROI extraction scheme integrates the effect of the local neighborhood and allow it to influence the membership value of each pixel. A new Hybrid FCM (H-FCM) algorithm is proposed, which integrates spatial information with a 2D adaptive noise removal SS-FCM model. Experiments have been conducted to verify the proposed model. Experiments showed that this proposed model produced high performance in ROI detection under different effects and on different types of retina images. Moreover, the results showed high sensitivity compared with recent researches.**

Keywords— eye fundus, diabetic retinopathy, exudates, fuzzy c-means, ROI.

I. Introduction

In the recent years, there has been a dramatic increase in the number of diabetic patients suffering from diabetic retinopathy. Patients with uncontrolled diabetes often develop ophthalmic complications, as corneal abnormalities, glaucoma, iris neovascularization, cataracts, and appearing of yellowish spots on the retina [1-4]. In some cases careful management of diabetes is the best way to prevent vision loss. Diabetic Retinopathy (DR) is an eye ailment which influences eighty to eighty-five percent of the patients who have diabetes for more than ten years. Having diabetes, obligates the patients to examine the retina [4] — even if their vision seems fine

DR is one of the most chronic diseases which make the key cause of vision loss in middle-aged people in the developed world [2]. Diabetic Retinopathy is a progressive eye diseases that causes changes in the blood vessels of the retina which may cause blindness if not prevented and treated at early stage. Diabetic retinopathy is one of the complications caused by diabetes and it appears in the retina, which is the tissue responsible for the vision in the eye [3].

The early detection and diagnosis is essential to save the vision of diabetic patients. The indications of diabetic retinopathy on the surface of the retina are micro-aneurysms, hemorrhages and exudates. The identification of exudates by Ophthalmologists normally requires dilation of pupil's eye using a chemical solution which consumes lot of time and affects patients [4].

Exudates are nothing but oily formations leaking from the poor end blood vessels [5]. Starts emerging, the DR is termed as moderate non-proliferative diabetic retinopathy. If these exudates start developing around the central vision area, it is called as diabetic maculopathy. After a certain time, when the retinopathy increases, the blood vessels get blocked by the infarcts in the retina. These small infarcts are known as soft exudates [4]. When the presence of the above three abnormalities are encountered together, this kind of retinopathy is then termed as severe non-proliferative diabetic retinopathy" [1]. Several techniques have been used to detect and classify diabetic retinopathy [6] [10]. In this research, the aim is to segment the ROI in the retina fundus images. Accurate automatic segmentation of retinal blood vessels from retina fundus images would be a tool for medical diagnostics [7] [11].

This work is partitioned into five sections. First of all was the introduction. Section 2 is biological background to know the anatomy of eye fundus retina and the shape of ROI, followed by the Section 3 that presented the proposed system architecture and describes each of its stages, in Section 4 the experimental results obtained during this work. At the end of this research Section 5 forms the conclusion of this research and outlines future work that would be done.

II. Biological Background

This section showed a biological background of the retina fundus and how it is affected by diabetes as shown in figure 1. The retina is a thin layer at the back of the eyeball. The retina holds the optic disc as shown in figure 1 (a). Around the optic disc there are the most of blood vessels. Blood vessels supply the retina. Optic disc is the bright hole located at the back of the eye.it is so close to the optic nerve that contains cells very sensitive to light, which trigger nerve impulses that pass via the optic nerve to the brain, where a visual image is formed [1]. The optic nerve has the responsibility of transferring visual and optical information to the vision centers of the brain. Around the optic nerve, there are the blood vessels (fig.1) where the blood supply should be efficient so that the cells of the retina get all they need to continue functioning. Also, as shown below the shape of yellowish spots known under the name of exudates. Exudates appear as yellowish spots and they are located in the posterior pole of the fundus image. Exudates are one of the main features of diabetic retinopathy system [1]. As the severity of the disease change the size and the shape of the exudates changes as shown in figure 1 (b).

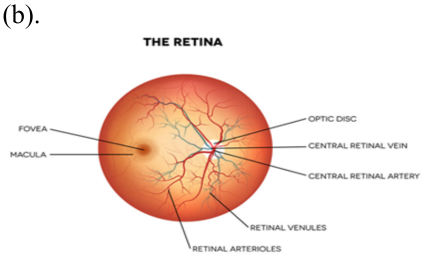

Figure 1.eye anatomy


Figure 1 (a). Optic disc

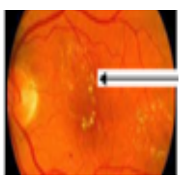
Figure 1 (b). Exudates

III. Proposed Model for Exudates Segmentation

This section presents the proposed model that has been used in bright abnormalities detection as shown below in figure 2.

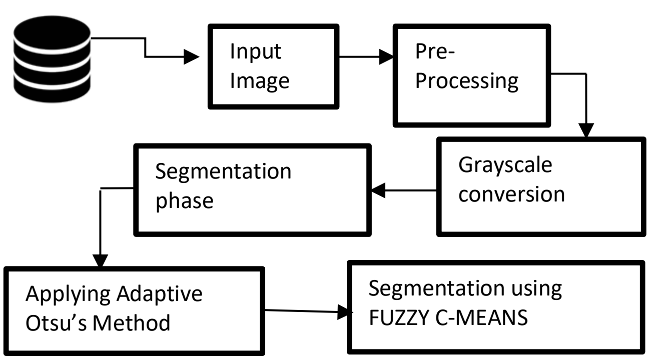

Figure 2. System Architecture

This system have diverse stage shown in figure 2. Image pre-processing passing through some conversion then to the Otsu's threshold, finally the ROI of exudates area affected were detected. This Model diagram of exudates detection based on Fuzzy C-means clustering and adaptive threshold.

A. *Convert to grayscale*

First of all the image is converted to Grayscale. Grayscale is reducing complexity: from a 3D pixel value (RGB) to a 1D value. Many tasks do not prosper with 3D pixel (e.g., edge detection) using the following function: rgb2gray (img) as shown in figure 3. [11].

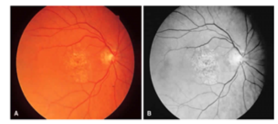
Figure 3.grayscale image

B. *Segmentation Phase*

Eliminating the background is an important step in this model to know the outlines of the retina in the sample image to facilitate next step of applying Otsu's thresholding as shown in the next sub-section in figure 4 [9].

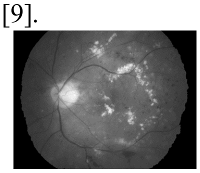
Figure 4. Removing background

C. *Adaptive thresholding using Otsu's Method*

In this sub-section applying Otsu's threshold method [8] involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. The idea of threshold is to apply a boundary-finding method, sample of the histogram that are only near where the boundary probability is high. The benefit of threshold is to separates the pixels in ways that tend to preserve the boundaries. Besides that, other scattered distributions within the object or the background are irrelevant. The advantages of threshold can be declared that it is simple to implement, fast especially if repeating on similar images and it is good for some kinds of images such as documents. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum. Using this method was very efficient because it is an adaptive threshold, it changes due to each image and due to the brightness and the infection affecting the retina. It is a base for the last step which is the clustering using the fuzzy c-means the aim is to find the threshold value where the sum of foreground and background spreads is at its minimum. Using this method was very efficient because it is an adaptive threshold, it changes due to each image and due to the brightness and the infection affecting the retina. It is a base for the last step which is the clustering using the fuzzy c-means as shown in figure 5.

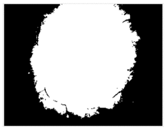

Figure 5. Otsu's threshold

D. The Proposed Fuzzy C-means clustering

In the medical application scenario, an ROI extraction scheme is needed to preserve image quality and to keep the ROI intact. A semi-supervised FCM algorithm (SS FCM) was introduced by [21] which allows the incorporation of expert knowledge into the FCM model. An expert defines a set of crisp labeled pixels that guide the clustering process. [24]. labeled pixels as:

$$P = \{p^{l}{}_{1},\ldots,p^{l}{}_{nl},\ p^{2}{}_{1},\ldots,p^{2}{}_{n2},\ p^{c}{}_{1},\ldots, \quad (3)$$
$$p^{c}{}_{nc}|p^{u}{}_{1},\ldots,p^{u}{}_{nu}\} = p^{l}\ U\ p^{u}$$

The superscripts represent the class numbers with maximum c classes specified by the training data, u represents unlabeled pixels and n_i denotes the number of pixels belonging to class i. The total number of pixels equals n where $n = n_l + n_u$. The fuzzy c-partition matrix of P has the following form:

$$U^{u} = \{u^{u}{}_{ik}\}\ \text{labeled}\ |U^{u} = \{u_{i}\ k^{u}\}\ \text{unlabeled} \quad (4)$$

U^u is initialized randomly while the membership values in U^l are hard labeled beforehand. The provided $u^{l}{}_{ik}$ are used to compute an initial set of "well seeded" cluster prototypes $u^{0}{}_{1\rightarrow 3}$

$$u\ i,0 = \frac{\sum^{nl}{}_{k=1} (u^{l}{}_{ik})^{m}\, p^{l}{}_{k}}{\sum^{nl}{}_{k=1} (u^{l}{}_{ik})^{m}} \quad (5)$$

If $n1 = 0$ or $w = 0$, it reduces to conventional FCM. 2D Wiener filter estimates the local mean and variance around each pixel as in Eqs (6) and (7):

$$\mu = \frac{1}{n\,m} \sum_{i\,j\,\in N B} I(i, j) \quad (6)$$

$$o2 = \frac{1}{nm} \sum_{i,j\in NB} I(i, j)2 - u2 \quad (7)$$

Where i and j belong to $n \times m$ neighborhood around each pixel of image I. An estimate for each pixel in filtered image FI is computed as follows:

$$FI(r, c) = u + \frac{o2 - w}{o2} \quad (I(r, c) - u) \quad (8)$$

Where w is the average of all the local estimated variances. Another adopted approach, is to create weighted sum intensity image using LAWS level mask [22]. The 2D convolution is given by:

$$WI(r, c) = \sum_{i=r-2}^{r+2} \sum_{j=c-2}^{c+2} NL5L5\ (i, j) * I\ (i, j) \quad (9)$$

Where

$$NL5L5 = 1/36 \begin{pmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{pmatrix}$$

$r=0, 1, 2\ldots N,\ c=0, 1, 2\ldots M$ and $*$ denotes 2D (9)

A spatial function defined as:

$$S_{ik}{}^{u} = \sum_{j\in NB(pk)} u_{ij} \quad (10)$$

NB (pk) represents a square 5 × 5 window centered at pixel pk. The spatial function is included within the membership function using the following formula:

$$u^{u}{}_{ik} = \frac{u_{ik}{}^{u}\, s_{ik}{}^{u}}{\sum^{c}{}_{j=1}\ u_{ij}{}^{u}\, s_{jk}{}^{u}} \quad (11)$$

In the first pass the membership function $uu\ ik$ is calculated as in Eq. (5) in the spectral domain. The spatial function is incorporated into $Uu\ ik$ in the second pass as in Eq. (10) to reflect the mapping of the pixels into the spatial domain. After the convergence of the clustering process, a defuzzification step is required to provide hard labels method is used to obtain our segmented image.

E. Segmentation using Fuzzy clustering

This is last section showing the final step in Fuzzy c-means clustering. (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters [13]. The emergence of these zero values would make similarity measure that does not accurately reflect the color difference between images and statistical histogram method to quantify more sensitive parameters as shown below in figure 6

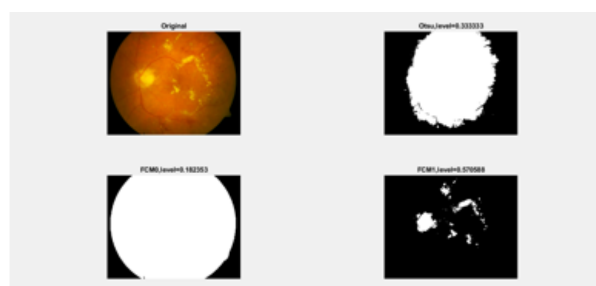

Figure 6. Segmentation Result

IV. EXPERIMENTAL RESULTS

A. Experimental Environment

The work was tested in a special conditions composed of 619 images from 3 datasets having different properties. This set of heterogeneous images help us to improve the accuracy and the robustness of this algorithm.

B. Input Dataset: fundus images

DIARETDB0: *Dataset Description:* contained 130 fundus images, of which 22 were normal,

DIARETDB1**:** *Dataset Description:* contained 89 fundus images, of which 5 only are normal and 84 contained signs of diabetic retinopathy.

MESSIDOR: *Dataset Description:* The dataset contained 1200 images packaged in three sets, each 100 images.

C. Exudates Segmentation Results

The proposed detection system adopted a two-stage approach for segmenting the bright abnormalities [15]. First, the fundus image was partitioned into clusters based on its adaptive threshold using Otsu's Method. Second, the pixels within the brightest cluster were threshold to remove the background and the non-bright pixels and preserve only the brightest ones within the cluster. The bright yellowish optic disc is usually clustered together with the other bright yellowish abnormalities and cotton wool spots. Therefore, the optic disc was detected by Hough transform from the fundus image to improve the detection of such bright abnormalities and thereby avoid the false response so that the bright lesions would not be misclassified or confused with the optic disc [14] [16]. As shown in figure 6.

D. Results of the proposed method for segmented the bright abnormalities relative to another model

Table 1 clusters and compares the results obtained by this model approach over the three different datasets, in terms of the sensitivity with a recent research. The table showed that the proposed system has a higher performance of 10.28% using images from DIARETRDB0. While using input images from MESSIDOR and DIARETDB1 the system illustrated 4.9% of improvement in sensitivity compared by Allam et al. [16].

Table1

#	Data set	No. of images	Abnormal img	Allam et. Al[33]		Our model	
				correct resp	sensitivity	correct img	Sensitivity
1	DIARETDB 0	130	86	68	0.7907	75	0.8720
2	DIARETDB 1	89	49	40	0.8163	42	0.8571
3	MESSIDOR	400	145	130	0.8966	135	0.9310
4	All Datasets	619	280	238	0.8345	252	0.8867

Experiments have been carried out to illustrate the performance of the proposed retinal eye fundus diagnoses model. The performance is evaluated in case of different types of images. Experimental results have been analyzed and discussion was proposed to demonstrate the improvement of the model.

E. Comparison of the proposed method of segmenting the bright abnormalities against others

Table 2 show a comparison between the proposed model and other previous model using another techniques, and different pre-processing in fundus image analysis. The table has some model tested on several datasets and a big number of images under different condition [16]. In the following table this proposed model showed an improvement in Sensitivity rate exceeded 7.5% testing it on different datasets.

Experimental results show that the model is robust to different types of images. The results show acceptable sensitivity rates between data sets. The system manifests considerable processing time against other researches. The model outperformed recent models in literature and achieved a high level of accuracy.

Table2

#	Detection Approach	Dataset(s)	Sensitivity
1	Harangi et. Al., (2012) [38]	DIARETDB1	0.6300
2	Eadaghi & Pourreza, (2012) [39]	DIARETDB1	0.7828
3	Franklin & Rajan, (2014) [40]	DIARETDB1	0.9630
4	Liu et al., (2017) [41]	DIARETDB1	0.8300
		DIARETDB0	0.7907
5	Allam et. Al.,(2017) [33] : color-based k-means clutering & statistics-based thresholding	DIARETDB0	0.7907
		DIARETDB1	0.8163
		MESSIDOR	0.8741
6	*Proposed method: Segment the candidate optic disc within the dectection of optic nerve surrounding by blood vessels*	DIARETDB0	0.8720
		DIARETDB1	0.8571
		MESSIDOR	0.9310

V. CONCLUSION

In this paper, an improved model has been introduced for eye disease detection system. From the perspective of the datasets utilized in segmenting the landmarks and abnormalities, DIARETDB 0, DIARETDB 1 and MESSIDOR were also frequently used by other algorithms in the literature were considered the benchmark for most of the segmentation algorithms in the literature. However, other fundus datasets Thereby, the proposed work exploit some of these mentioned datasets, creating an exceptional and unique experimental environment.

Obviously, the pre-processing techniques led to quicker and more accurate results at the further segmentation stage. For instance, the fundus images in the presented algorithm were initially converted to grayscale in order to facilitate the next step. Although, some of the datasets provided binary images, while other datasets did not.

Abnormalities such as Exudates and cotton wool spots are mainly characterized by their bright yellowish colour. But on the contrary the optic disc, such abnormalities have varying sizes, irregular shapes, and random locations within the fundus. Accordingly, it was impractical for the same approach of detecting the optic disc to be reutilized for extracting those bright abnormalities.

The proposed method adopted two stage approach for segmenting the bright abnormalities occurring in pathological fundus images. Thus, the overall process of detecting and segmenting those abnormalities by those two stages. The first stage is to use the Otsu's adaptive threshold applied on binary image in order to remove the relatively non-bright pixels and preserve only the bright ones within the cluster. The second stage partitioned the fundus image into several clusters using FCM to get best result for overlapped data set and comparatively better then k-means algorithm. FCM is unlike k-means where data point must exclusively belong to one cluster centre: here data point is assigned membership to each cluster centre as a result of which data point may belong to more than one cluster centre.

This proposed method was tested and evaluated over DIARETDB0, DIARETDB1 and MESSIDOR containing different types of abnormal images. The proposed system correctly detected the bright abnormalities, such as hard exudates and cotton wool spots, achieving comparable average sensitivity rates of 91.04%. This computer-aided model achieved better results in eye diagnosis detection compared with recent researches with improvement reach exceeded 7.5%.

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