A Fuzzy Architecture for Detecting Suspect Diabetic Symptoms in Retinal Images

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Abstract:
In this paper a contribution to the detection of suspect diabetic symptoms in fundus images is proposed by synthesizing a fuzzy architecture for retinal image processing based on a contrast enhancement of retinal images. Fuzzy parameters of the architecture are determined by maximizing a proper index. Enhanced contrast images are then properly segmented to isolate suspect areas by a proper thresholding, which minimizes classification errors. In output images, suspect diabetic regions are clearly represented. Capabilities and performances of the proposed architecture are illustrated and compared to results obtained in literature.

Key-Words: - Fuzzy techniques, Diabetic retinopathies

1 Introduction

In ophthalmology attention has been recently focused on the problem of developing a diagnostic support for the detection of symptoms related to diabetic rethinopathies [1]. It is well known that these diseases can be revealed by specific symptoms, called *exudates* or *drusen* or *cotton wool spots*, which appear as bright areas in digital retinal images. On this proposal, some interesting contributions have already been proposed in [2, 5]. In [2] the detection of diabetic symptoms is achieved by processing a retinal image by means of a median filter when domain knowledge about brightness is available. Unfortunately, drawbacks arise due to the number of variables, like type and dimensions of filters to be evaluated. In [3] symptoms are classified by a Support Vector Machine (SVM) structure, but the results provided by this system are not satisfactory if the illumination of the image is not uniform. This drawback is overcome in [4], where exudates are revealed by combining techniques of region growing and edge detection. Such an approach gives interesting results, but it depends on a heuristic choice of three thresholds during a region growing step and heavy computational burden is needed to process two layers of the retinal image. In [5] suspect regions are detected segmenting images by a fuzzy C-means clustering technique. In this case, fuzzy logic reveals effective, but the proposed algorithm could reveal quite sensitive to the choice of the selective features and colour space representation. For this reason, synthesis criteria, which are independent from environmental conditions and able to evaluate system parameters in the acquisition of retinal images, reveal fundamental.

On the basis of these considerations and taking into account [6], in this work a contribution to the detection of suspect diabetic symptoms by synthesizing a fuzzy architecture for retinal image processing is proposed. In particular, the maximization of a proper correct classification rate index is suggested to evaluate required fuzzy parameters. Then, a thresholding step is performed to evaluate an optimal threshold which can minimize pixel classification errors. Enhanced contrast images are successively globally segmented, providing binary output images, in which suspect areas are isolated Finally, the capabilities of the proposed architecture are illustrated by means of experimental examples and the performances of the whole system are compared to results obtained in literature.

2 Model of the System

The input of the whole system is given by the green layer $\boldsymbol{I}$ of an RGB retinal image, due to the fact that such a layer presents maximum contrast. Vague bright areas, suspected to be diabetic symptoms, have to be detected in image $\boldsymbol{I}$.

In Fig. 1 the block diagram of the proposed

architecture is shown.

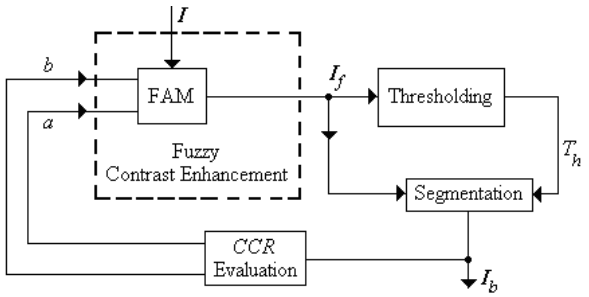


Fig.1: Block Diagram of the proposed Architecture

An adequate image segmentation has to be carried out in order to segment each *fundus* image in two Suspect/Not-Suspect sets, each one supposed as distinguishing a clinically significant area. Therefore, a proper threshold has to be chosen in order to classify pixels belonging to the latter and the former set. To this purpose, a fuzzy contrast enhancement step is firstly performed to obtain images $\boldsymbol{I_f}$, whose histograms are bimodal. Such property makes the successive evaluation of a threshold T_h feasible. Image $\boldsymbol{I_f}$ can be then segmented by the value T_h, yielding binary output images $\boldsymbol{I_b}$, in which suspect regions and not suspect ones are represented by different gray levels.

2.1 Fuzzy Contrast Enhancement

Contrast enhancement should be achieved preserving anatomic details, like symptoms to be detected, in digital retinal images. To this purpose, in this paper, the fuzzy procedure proposed in [6] is considered. In detail, a Fuzzy Associative Memory (FAM) is developed, by defining two fuzzy antecedent sets and two fuzzy consequent ones adequate to describe the semantic content of retinal images. Each image $\boldsymbol{I}$ is considered as formed by two partially overlapped input fuzzy subsets, called *Deep* **D** and *Pale* **P**, respectively, defined as:

$$\mathbf{D} = \{\mathrm{D}(g) = m_{\mathrm{D}}(g) \mid 0 \le g \le b\}$$
$$\mathbf{P} = \{\mathrm{P}(g) = m_{\mathrm{P}}(g) \mid a \le g \le 255\}$$

with $0 \le a < b \le 255$, being $g = 0, \ldots, 255$ the generic grey value of each pixel. Right-angled triangular membership functions are adopted for $m_{\mathrm{D}}(g)$, $m_{\mathrm{P}}(g)$ with values in [0; 1]. In an analogous way, the domain of output values in [–1; 1] is quantized into two output *Not-Suspect/Suspect* **NS**/**S** fuzzy subsets, respectively. Basing on the assumption that pale areas can represent suspect retinal damages, the fuzzy rules which provide a proper mapping from input images into output contrasted ones can be expressed as:

$$\text{IF} \quad p_{ij} \in \mathbf{D} \quad \text{THEN} \quad f_{ij} \in \mathbf{NS}$$
$$\text{IF} \quad p_{ij} \in \mathbf{P} \quad \text{THEN} \quad f_{ij} \in \quad \mathbf{S}$$

where p_{ij} and f_{ij} denote grey level values of each pixel in input images $\boldsymbol{I}$ and in contrast-enhanced ones $\boldsymbol{I_f}$, respectively. It is worth to notice that the choice of fuzzy parameters a and b, which identify the antecedent membership functions, reveals fundamental for the FAM behaviour, therefore, synthesis criteria for their evaluation have to be accurately established. For this purpose, the following Correct Classification Rate index *CCR%* is defined

$$CCR\% = 100 \frac{\text{Number of correctly classified pixels}}{\text{Total Number of pixels}} \quad (1)$$

considering all pixels belonging to clinically interesting regions. This index gives a percentage measure of the capability of the network to correctly classify regions.

Fuzzy parameters a and b have to be computed by maximizing index *CCR%*. The synthesized fuzzy system is able to enhance image contrast. In detail, each resulting image $\boldsymbol{I_f}$ presents a histogram given by the discrete function:

$$h_f(g): \quad g \rightarrow h_g \qquad g = 0, 1, .., 255$$

being $h_g = \text{cardinality}\{(i, j) \mid \boldsymbol{I_f}(i, j) = g\}$.

In each resulting image $\boldsymbol{I_f}$ contrast is maximum whereas the loss of information is minimum. This condition reveals optimal when suspect bright areas need to be detected. In particular, the histogram of $\boldsymbol{I_f}$ presents two-peaks. The former peak concerns with information about deep areas in images $\boldsymbol{I}$, the latter peak concerns with pale ones. Therefore, retinal suspect areas can be highlighted in each contrast-enhanced image $\boldsymbol{I_f}$ by an adequate adaptive segmentation.

2.2 Thresholding

The aim of this step consists in evaluating the optimal threshold which can minimize pixel classification errors. For this purpose, two functions which can approximate each one of the modes (the zones corresponding to two peaks) of the histogram $h_f(g)$ are considered.

In particular, let m denote the maximum gray

level in the range [1;254] such that $h(m)$ is a relative minimum of histogram $h_f(g)$. The following vectors can be defined:

$$\boldsymbol{g} = [1, 2, \ldots, 255]^T \in \mathbb{N}^{255x1}$$
$$\boldsymbol{h_D} = [\, h_1, \ldots h_k, \ldots h_m, 0 \ldots, 0]^T \in \mathbb{N}^{255x1}$$
$$\boldsymbol{h_P} = [\, 0, \ldots, 0, h_{m+1}, h_{m+2} \ldots, \ldots h_{255}]^T \in \mathbb{N}^{255x1}$$

containing occurrences of deep/pale gray level values only, respectively, and the matrices

$$\boldsymbol{H_D} = [\, \boldsymbol{g}, \boldsymbol{h_D}\,] \in \mathbb{N}^{255x2} \qquad \boldsymbol{H_P} = [\, \boldsymbol{g}, \boldsymbol{h_P}\,] \in \mathbb{N}^{255x2}$$

which contain information about deep areas and pale ones of contrast-enhanced images $\boldsymbol{I_f}$. Matrices $\boldsymbol{H_D}$ and $\boldsymbol{H_P}$ provide proper sets for obtaining two interpolating discrete functions $h_D(g)$ and $h_P(g)$, each one able to approximate one mode of the bimodal histogram $h_f(g)$.
The threshold T_h able to optimally segment $\boldsymbol{I_f}$ is evaluated as an intersection of such discrete functions, that is, when $h_D(T_h) = h_P(T_h)$.

2.3 Segmentation

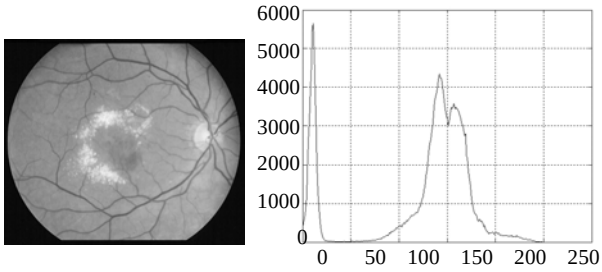
Segmentation is the final step of the proposed architecture, which generates output binary images containing only significant information about suspect damaged retinal areas.
In particular, $\boldsymbol{I_f}$ can be segmented as follows

$$\boldsymbol{I_b}(i,j) = \begin{cases} 255 & \text{if } \boldsymbol{I_f}(i,j) < T_h \\ 0 & \text{if } \boldsymbol{I_f}(i,j) \geq T_h \end{cases} \quad i = 0,, M,\ j = 0,., N$$

where the binary image $\boldsymbol{I_b}$ provides a detailed mask, in which black pixels identify suspect areas in the original *fundus* image $\boldsymbol{I}$.

3 Numerical Results

The capabilities of the proposed system have been investigated on several (450x530) retinal images, accurately selected by expert clinicians to constitute an "ad hoc" dataset of images with fundamental diabetic symptoms of different sizes, positions and colours. As an example, in Fig. 2 the green layer of a selected *fundus* image $\boldsymbol{I}$ and its histogram $h(g)$ are reported. Diabetic symptoms given by vague pale regions can be noted in this image. The values of the fuzzy parameters a and b are determined by maximizing the *CCR%* index as defined in (1). For this purpose, several values of the fuzzy parameters $a \in [25, 50]$ and $b \in [60, 255]$, respectively, have been considered.



(a) (b)

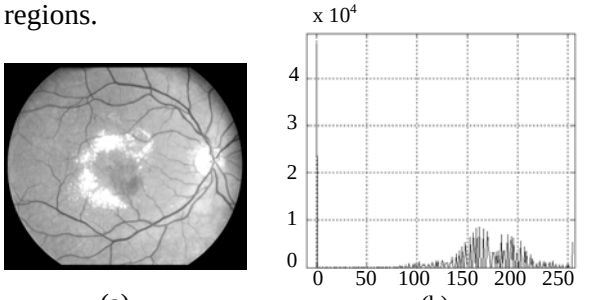
Fig.2: (a) Input *fundus* image $\boldsymbol{I}$; (b) its histogram $h(g)$

In Table I the values of *CCR* versus the fuzzy parameter b are reported for $a \in [25, 50]$. It can be noticed that the best values of *CCR%* can be obtained when b=220 and a=25.

Table I: - *CCR%* vs fuzzy parameters a and b

	a=25	a=30	a=35	a=40	a=45	a=50
b=60	38.10	38.00	38.00	38.00	38.00	38.00
b=80	38.10	38.00	38.00	38.00	38.00	38.00
b=100	38.18	38.13	38.13	38.13	38.13	38.13
b=120	39.17	39.08	39.17	39.17	39.17	39.17
b=140	41.87	41.77	41.77	42.50	42.50	42.50
b=160	61.70	61.61	61.61	61.61	61.61	64.91
b=180	82.89	85.50	85.50	85.50	85.50	85.50
b=200	97.85	97.61	97.42	97.42	97.42	97.42
b=220	98.36	98.26	98.26	98.18	98.09	98.09
b=240	96.89	96.79	96.79	96.79	96.79	96.73
b=255	96.18	96.09	96.02	95.96	95.91	95.91

Fig.3 shows the evaluated contrast-enhanced image $\boldsymbol{I_f}$ and its bimodal histogram obtained by processing image $\boldsymbol{I}$ with the presented fuzzy system. The peak value for g=254 in the histogram $h_f(g)$ summarizes bright damaged regions.

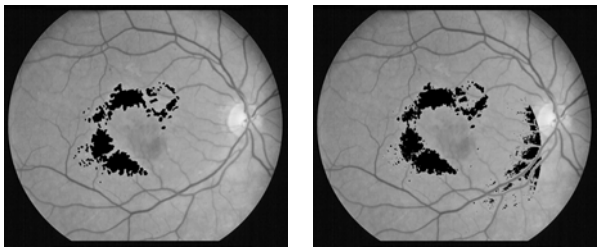


(a) (b)

Fig.3: (a) Image $\boldsymbol{I_f}$; (b) its histogram $h_f(g)$

Due to the bimodal behaviour of the histogram $h_f(g)$, an optimal thresholding has been successively performed. An optimal value T_h = 217 has been determined for segmenting image $\boldsymbol{I_f}$.
Quality performances of the system have been then evaluated by considering the so called *gold*

standard image, provided by expert clinicians and shown in Fig. 4. For the sake of a better comparison, in the same figure the image obtained by superimposing image $\boldsymbol{I_b}$ to fundus image $\boldsymbol{I}$ has also been reported. In both images suspect diabetic areas are indicated with black pixels.



(a) (b)

Fig.4: (a) Gold standard image; (b) Superimposition of image $\boldsymbol{I_b}$ to *fundus* image $\boldsymbol{I}$

Results can be discussed by determining the values of True Positives TP, True Negatives TN, False Positive FP and False Negatives FN, as defined in [1]. In detail, the quantity TP gives the number of pixels that the system correctly classifies as symptoms, when compared with reference results provided by expert clinicians in the gold standard image; the values FN and FP indicate wrongly classified pixels with respect to reference ones. Performances can be evaluated by computing *CCR*% expressed as:

$$CCR\% = 100\frac{(TP + TN)}{\text{Total Number of pixels}}$$

As reported in [4], the values of indices TN, FN, FP and TP are computed in a circular window of radius equal to 156 pixels, centered on the fovea. Such radius corresponds to a linear distance of about 6000μm, computed as 2DD, being DD the diameter of optic disc. Successively, the value of *CCR%* for the reported image (case A) has been compared to results obtained by the method in [2] as shown in Table II, case B.

TABLE II *CCR%* values: :case A); case B) .

A	B
95.24	98.00

As it can be noted, the value of *CCR%* herein evaluated for the presented system, can be considered as meaningful.

4 Conclusions

A contribution to the detection of suspect diabetic symptoms by means of a fuzzy architecture for retinal image processing has been proposed to highlights pale regions in *fundus* images of patients with diabetic pathologies. After evaluating an optimal threshold to minimize pixel classification errors, enhanced contrast images have been successively segmented, providing binary output images, in which suspect areas have been isolated. Quality performances of the proposed architecture have been finally evaluated and quite satisfactorily compared with results given in other studies.

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