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A Hybrid Neurofuzzy System for Contrast Enhancement of Fundus Images in Diabetic Retinopathies

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Abstract: - In the field of diabetic retinopathies attention has been recently focused on the problem of obtaining an accurate diabetic ocular diagnosis. In this paper a contribution in the detection of diabetic symptoms using contrast enhancement of fundus images is proposed by synthesizing an “ad hoc” neurofuzzy system. A fuzzy technique is considered to develop a suitable coding of fuzzy rules. A sparsely-connected neural network is then synthesized to provide enhanced contrast retinal images with bimodal histograms. Experimental examples are reported.

Key-Words: - Sparsely-connected Neural Networks, Fuzzy techniques, Diabetic retinopathies

1 Introduction

In the field of diabetic retinopathies attention has been recently focused on the problem of obtaining an accurate diabetic ocular screening [1,2]. It is well known that diabetic retinopathies can be revealed by specific symptoms, called *exudates, drusen* and *cotton wool spots*, which appear as pale areas in digital retinal images.

On this proposal, some interesting contributions aiming at the development of diagnostic tools for automatic identification and classification of such symptoms in fundus images have already been proposed in [1], [3-6]. In [1] exudates, drusen and cotton wool spots are detected by computing an intensity difference map with a median filter. In [3] a first approach to the detection of exudates by means of neural networks is reported, but obtained performances greatly depend on the number of images in the training set. In [4] a recursive region growing segmentation algorithm is used for the detection of exudates. In particular, each pixel of a retinal image is classified as belonging to a suspected region only if: (*i*) it belongs to the neighbourhood of a pixel which is in a suspected area and (*ii*) its grey level belongs to a pre-specified range of a representative centre. In this way, clinicians’ recommended standards are achieved, but condition (*ii*) is satisfied only if an *a priori* knowledge of image contrast or brightness is available. In [5] colour retinal images are segmented using a fuzzy C-means clustering technique in order to group close pixels with similar colours. In this case fuzzy logic reveals effective, but the proposed algorithm is quite sensitive both to selective features and colour space representation. Unfortunately, in cited papers often drawbacks arise for the variables to be evaluated, e.g., filter type and dimension.

By considering that the use of neural networks revealed successful for several medical image processing applications, in this paper the synthesis of a hybrid neurofuzzy system is proposed for highlighting diabetic symptoms using contrast enhancement of fundus images. In detail, a fuzzy procedure is firstly developed in order to enhance the contrast in a retinal gray image of a patient with a diabetic pathology. Then, a sparsely-connected neural network is designed by adopting the synthesis procedure developed in [7] to behave as the fuzzy procedure reports. Final outputs are contrast enhanced images, in which pale areas can reveal suspected diabetic symptoms. The capabilities of the proposed hybrid neurofuzzy system are illustrated by means of experimental examples.

2 Model of the Hybrid System

The model of the proposed neurofuzzy system is shown in Fig. 1.

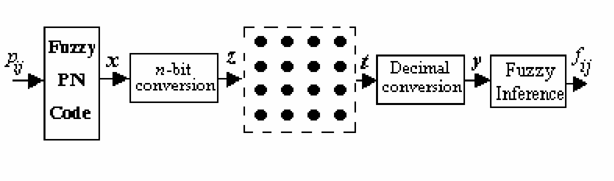

Fig.1: Block diagram of the hybrid system

The input of the whole architecture is given by the green layer $\boldsymbol{I}_{\mathbf{g}}$ of the generic RGB retinal image. Pale areas, suspected to be diabetic symptoms, should be detected in these images $\boldsymbol{I}_{\mathbf{g}}$,. For this purpose, image segmentations into two levels have generally to be carried out in order to segment the generic *fundus* image in two sets, each one supposed as distinguishing a significant area from a symptomatic point of view. Unfortunately, an automatic selection of such a threshold is not easy to obtain, due to the vagueness of images $\boldsymbol{I}_{\mathbf{g}}$ and to their strongly nonlinear histograms. However, a threshold selection can be not computationally expensive if the considered image histogram is bimodal, that is, the sets to be identified have the maximum distance in brightness space. For this reason, a suitable neural network, working as a fuzzy system is developed to obtain images $\mathbf{I}_{\mathbf{f}}$ from $\mathbf{I}_{\mathbf{g}}$ with bimodal histograms as shown in the next section.

3 Fuzzy Encoding Procedure

Contrast enhancement of digital retinal images should be achieved preserving anatomic details. In this paper, a fuzzy system, based on two fuzzy IF-THEN rules, is developed, with the aim of classifying each pixel of the generic retinal image $\boldsymbol{I}_{\mathbf{g}}$ as belonging to a suspect set or to a not-suspect one. For this purpose, two fuzzy antecedent sets and two fuzzy consequent ones adequate to describe the semantic content of a retinal image are defined. In detail, the discrete universe of discourse of grey level values between 0 and 255 is considered as formed by two overlapped input fuzzy subsets, called Deep **D** and Pale **P**, respectively, defined as:

$$\mathbf{D} = \{\mathrm{D}(g) = m_{\mathrm{D}}(g) \mid 0 \le g \le b\} \qquad (1)$$

$$\mathbf{P} = \{\mathrm{P}(g) = m_{\mathrm{P}}(g) \mid a \le g \le 255\} \qquad (2)$$

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

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

where p_{ij} and f_{ij} denote the grey level values of each pixel in input images and in contrast-enhanced ones, respectively.

As shown in [7], the reported fuzzy rules can be encoded by determining a weight matrix **W** based on a max-bounded-product composition (max-⊗) Then, a vector $\boldsymbol{y}(p_{ij}) = [y_1(p_{ij})\ \ y_2(p_{ij})]^T$, whose components take into account the activation of the first/second rule, respectively, is evaluated by means of an operation of max-bounded-composition. The components $y_1(p_{ij})$ and $y_2(p_{ij})$ are successively inferred to obtain pixels f_{ij} of output images by:

$$f_{ij} = \frac{255}{2}\left(\frac{-y_1(p_{ij}) + y_2(p_{ij})}{y_1(p_{ij}) + y_2(p_{ij})} + 1\right) \qquad (3)$$

In this way the histogram of $\boldsymbol{I}_{\boldsymbol{f}}$ is emphasized toward the extreme values of vector $\boldsymbol{g}$ with respect to the original image and contrast enhancement is achieved.

4 Hybrid Neurofuzzy System

A neural network, behaving as the just codified fuzzy block for contrast enhancement, can now be synthesized. The training data set has to be formed by input/output pairs which codify the previously defined fuzzy rules. In detail, let the (4x2)-matrix **W** be the weight matrix of the neural network to be synthesized [7]. The generic pair $(\boldsymbol{x}^g; \boldsymbol{y}^g)$ can be defined by considering

$$\boldsymbol{x}^g = [m_{\mathrm{D}}(g)\ \ m_{\mathrm{D}}(g)\ \ m_{\mathrm{P}}(g)\ \ m_{\mathrm{P}}(g)] =$$
$$= [x_1^g\ \ x_1^g\ \ x_2^g\ \ x_2^g] \in \Re^{1x4}$$

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$$\boldsymbol{y}^g = \boldsymbol{x}^g \otimes \mathbf{W} \tag{4}$$

with $\boldsymbol{y}^g = [y_1^{\,g}\, y_2^{\,g}] \in \mathbb{R}^{1x2}$ $\qquad g=0,..,255.$

It should be observed that the components of vectors $\boldsymbol{x}^g$ and $\boldsymbol{y}^g$ assume values corresponding to the activation of the fuzzy rules and their outputs. More in detail, each input vector $\boldsymbol{x}^g$ contains the values of membership functions $m_D(g)$, $m_p(g)$ for each $g \in [0, 255]$ and is associated to an output vector $\boldsymbol{y}^g$**.** The generic component of vector $\boldsymbol{x}^g$ can assume one among 256 fuzzy values in [0, 1] for each gray level of the considered original image. Moreover, the components of the output vector $\boldsymbol{y}^g = [y_1^{\,g}, y_2^{\,g}]$ can assume only two fuzzy values corresponding to the activation of the outputs **NS/S**, respectively. The two outputs y_1^g and y_2^g are inferred with the well-known method of the centre of gravity to obtain a fuzzy value f_{ij} for each value of g and for each pixel of output image $\boldsymbol{I_f}$.
A suitable training set **T** for the learning phase of the proposed neurofuzzy system can be obtained in the following way. The elements $x_1^{\,g}$ and $x_2^{\,g}$ are converted into the following 2^3-bit bipolar vectors $\mathbf{z}_1^{\boldsymbol{g}}$, $\mathbf{z}_2^{\boldsymbol{g}}$ to be considered as inputs to the sparsely-connected neural network

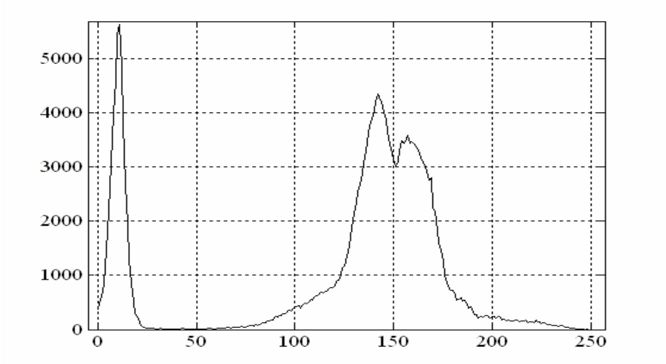
$$\mathbf{z}_1^{\boldsymbol{g}} = [z_1^{\,g}, z_2^{\,g}, \ldots, z_n^{\,g}] \in \{-1,1\}^{1xn}$$
$$\mathbf{z}_2^{\boldsymbol{g}} = [z_{n+1}^{\,g}, z_{n+2}^{\,g}, \ldots, z_{2n}^{\,g}] \in \{-1,1\}^{1xn}$$

with $n = 2^3$. The outputs of the neural network are given by two bipolar 2^3-bit vectors $\boldsymbol{t}_1^{\boldsymbol{g}} = [t_1^{\,g}, .., t_n^{\,g}] \in \{-1,1\}^{1xn}$ and $\boldsymbol{t}_2^{\boldsymbol{g}} = [t_{n+1}^{\,g}, t_{n+2}^{\,g}, \ldots, t_{2n}^{\,g}] \in \{-1,1\}^{1xn}$ which are to be converted in a decimal notation to obtain the vector $\boldsymbol{y}^{\mathbf{g}}$. In this way, the bipolar input vector $(\boldsymbol{z}^g)^T = [(\boldsymbol{z}_1^{\,g})^T \;\; (\boldsymbol{z}_2^{\,g})^T]^T \in \{-1,1\}^{2nx1}$ and output vector $(\boldsymbol{t}^g)^T = [(\boldsymbol{t}_1^{\,g})^T \;\; (\boldsymbol{t}_2^{\,g})^T]^T \in \{-1,1\}^{2nx1}$ uniquely identify the corresponding vectors $\boldsymbol{x}^{\boldsymbol{g}}$ and $\boldsymbol{y}^{\boldsymbol{g}}$. Therefore, the set $\mathbf{T} = \{[(\boldsymbol{z}^g)^T \;\; (\boldsymbol{t}^g)^T], g = 0, \ldots, 255\}$ properly codifies previous fuzzy rules, and is considered as a suitable training set for the learning phase of the proposed neurofuzzy system. The capabilities of the designed neurofuzzy system are confirmed when images to be processed are submitted to the network during the validation phase.

5 Numerical Results

The capabilities of the designed neurofuzzy architecture have been investigated on several (450x530) retinal images. In Figs.2 (a)-(b) the green layer of a selected *fundus* image $\boldsymbol{I_g}$ and its corresponding histogram are reported, respectively. In Fig.2(a) vague pale regions can be noted in the reported image.

(a)

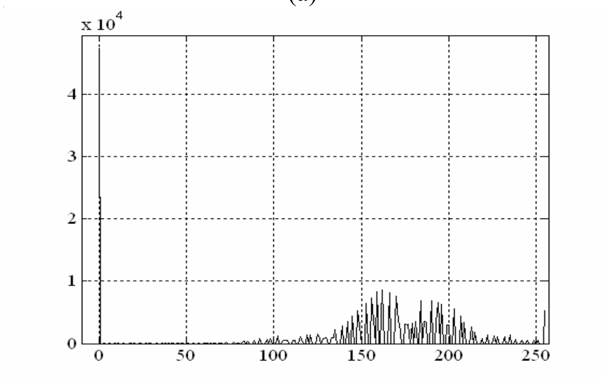


(b)

Fig.2: (a) Selected *fundus* image $\boldsymbol{I_g}$;
(b) its histogram

The proposed neural system has a Hopfield-type sparsely-connected architecture, whose neurons are arranged in a (4x4)-grid structure with a neighbourhood of order r=1. Moreover, each neuron is characterized by a piecewise linear output function. During the training phase, input/output pairs belonging to the training set **T** have been submitted to the neural network to be synthesized. Interconnection weights have been determined following the learning algorithm reported in [7]. Several values of the fuzzy parameters $a \in [25, 50]$ and $b \in [60, 255]$, respectively, have been chosen. Following the reported design procedure, a (4x4)-neurofuzzy architecture has been synthesized for each ordered pair (a, b). The bimodality test reported in [8] has been correspondently applied to determine the value of the valley-to-peak ratio δ. Figs.3 (a)-(b) show the optimal enhanced-contrast image $\boldsymbol{I_f}$ and its bimodal histogram with the minimum value $\delta = 0.3074$, obtained by processing the image $\boldsymbol{I_g}$ (with $\delta=1$) using the designed neurofuzzy system, being a=25 and b=200. By considering that an amount of close pale pixels indicates suspect areas, the peak value equal to 5919 pixels in the histogram of $\boldsymbol{I_g}$ provides a measure of dimensions of suspect areas in the retinal image.

(a)



(b)

Fig. 3: (a): Enhanced contrast image $\boldsymbol{I_f}$;
(b) its histogram

Moreover, due to the fact that the histogram presents a bimodal behaviour, an automatic choice of a threshold results feasible. As an example, following the procedure reported in [9] a threshold t_h=217 has been evaluated. In Fig.4 a bipolar output image is shown, where black pixels represent areas that can be classified as suspected symptoms or anatomic details. As it can be observed, almost all suspected areas can be successfully detected.

Figs.4: An example of segmentation for t_h=217.

6 Conclusions

In this paper a contribution in the detection of diabetic symptoms using contrast enhancement of fundus images has been proposed by synthesizing a hybrid neurofuzzy system via a sparsely-connected neural network. Final outputs are contrast enhanced images, in which pale areas can easily reveal suspected diabetic symptoms. The synthesized neurofuzzy system provides contrast-enhanced images with bimodal histograms, which are suitable for successive image segmentations and measurements of the gravity of diabetic symptoms. This represents a significant step in the direction of prevention and patients' follow up. Satisfying results have been reported.

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