An Intelligent System for Improving Detection of Diabetic Symptoms in Retinal Images
Leonarda Carnimeo, Antonio Giaquinto

Abstract: In this paper a contribution towards an automatic detection of diabetic symptoms in retinal images is proposed by synthesizing an intelligent system for retinal image processing in diabetic retinopathies. Image contrast is firstly enhanced by means of a neurofuzzy subsystem, where properly codified fuzzy rules are implemented using a sparsely-connected (4x4)-cell Hopfield-type neural network. Enhanced contrast images are then properly segmented to isolate suspect areas in binary output images after computing the optimally global threshold by a NN-based subsystem. Enhanced contrast images are properly segmented to isolate suspect areas in binary output images after computing the optimally global threshold by a NN-based subsystem. In bipolar output images, suspect diabetic areas are quite satisfactorily isolated. System performances are evaluated by means of an adequate index to provide percentage measures in the detection of eye suspect regions. Results are discussed and successively compared with results from other researchers. Future work is suggested as improvement of the proposed intelligent system for behaving as a diagnostic support tool.

Key words: Intelligent systems, Artificial neural networks, Fuzzy techniques, Diabetic Retinopathies

I. INTRODUCTION

It is well known that diabetic retinopathies can be revealed by specific symptoms, such as hard exudates, drusen and cotton wool spots, which appear as pale areas in retinal images [1], [2]. Contributions aiming at the development of diagnostic tools for an automatic identification of such symptoms in fundus images have been recently proposed [3]-[5]. In [3] a first investigation about the use of neural networks to achieve detection of diabetic symptoms in fundus images is carefully reported. In [4] an approach based on fuzzy techniques has been considered for colour fundus image segmentations, but the proposed algorithm is quite sensitive both to selective features and to colour space representation. In [5] the detection of optic disk and exudates in retinal images is carried on by means of a multilevel thresholding technique, but a further processing step of valley search in histograms is required. Moreover, different contributions to the detection of symptoms using neural networks have been developed in [6]-[8]. In [6], [7] Multi-Layer Perceptron neural networks (MLP) have been trained for classifying diabetic symptoms both by selecting proper image features as training data sets and by developing a specific component analysis. Synthesized networks reveal effective, but heavy computational efforts are required.

Furthermore, in [8] a network of spiking neurons have been considered to detect symptoms in segmented retinal images, but drawbacks arise for high memory requirements and long computation times.

In this paper, a contribution for improving the detection of diabetic exudates is proposed by synthesizing an intelligent system for retinal image processing. In detail, the model of a hybrid system of neural networks is introduced. A sparsely-connected neural network is firstly developed to behave as a fuzzy system to highlight pale regions in fundus images of patients with diabetic pathologies. A synthesis procedure developed by the same authors in [9] is adopted. Then, a subsystem of Multi-Layer Perceptron neural networks is trained using more algorithms for evaluating the optimal global threshold which can minimize pixel classification errors. Enhanced contrast images are successively segmented, providing bipolar output images, in which suspected diabetic symptoms are clearly isolated. Performances of the whole system are evaluated. The capabilities of the proposed intelligent system are illustrated and discussed by means of experimental examples.

II. MODEL OF THE INTELLIGENT SYSTEM

The proposed intelligent system implements three image processing steps:
- Neurofuzzy Contrast Enhancement;
- NN-based Threshold Computation;
- Globally Optimal Segmentation

as reported in Fig.1 and described in the following.

![Fig.1. Model of the proposed Intelligent System](image)

The input of the whole system is given by the green layer $I$ of an RGB retinal image. Vague pale areas, suspected to be diabetic symptoms, have to be detected in image $I$. For this purpose, 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. Unfortunately, an automatic computation of a proper threshold is not feasible,

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both for vagueness of pale regions and for the strong nonlinearity of histograms in fundus images \( I \). However, a threshold computation can be computationally effective if histograms of analyzed images reveal bimodal, that is, the two sets to be identified have the maximum distance in brightness space. This can be obtained via a neurofuzzy image contrast enhancement subsystem. For this purpose, a sparsely-connected neural network \( \text{NN}_f \), behaving as a fuzzy system, is herein implemented to process each image \( I \) and obtain a contrast-enhanced image \( I_e \) with a bimodal histogram as shown in Fig.2. Then, an optimal global threshold computation is developed by means of two MLP networks behaving as histogram interpolators. Finally, a globally optimal bipolar segmentation is performed on images \( I_e \), providing bipolar output images in which diabetic symptoms are highlighted.

In an analogous way, the domain of output values in \([-1; 1]\) is quantized into two output \( \text{Not-Suspect}/\text{Suspect} \) fuzzy subsets, respectively. Basing on the assumption that pale areas represent suspect retinal damages, the fuzzy rules which provide a proper mapping from input images into output contrasted ones can be expressed as:

\[
\begin{align*}
\text{If } p_y \in \text{D} & \text{ THEN } f_y \in \text{NS} \\
\text{If } p_y \in \text{P} & \text{ THEN } f_y \in \text{S}
\end{align*}
\]

where \( p_y \) and \( f_y \) denote grey level values of each pixel in input images \( I \) and in contrast-enhanced ones \( I_e \), respectively. All possible values that a generic pixel \( p_y \) can assume in \([0, 255]\) are codified by considering

\[
x_g = [m_D(g) \ m_D(g) \ m_P(g) \ m_P(g)] = [x_{g1} \ x_{g2} \ x_{g3} \ x_{g4}] \in \mathbb{R}^{1 \times 4} \quad g = 0, \ldots, 255
\]

As shown in [9], the reported fuzzy rules can be encoded by means of a \((4\times2)\)-matrix \( F \). An output vector \( y_g = [y_{g1} \ y_{g2}] \in \mathbb{R}^{1 \times 2} \) can be associated to each input \( x_g \) by considering

\[
y_g = x_g \otimes F \quad g = 0, \ldots, 255
\]

It should be observed that each input vector \( x_g \) contains the values of membership functions for each value of \( g \). The generic component of vector \( x_g \) can assume one among 256 fuzzy values in \([0, 1]\) for each gray level of image \( I \). Moreover, the components of output vector \( y_g \) can assume only two fuzzy values corresponding to the degree of membership to the subsets \( \text{NS}/\text{S} \), respectively. The elements \( y_{g1} \) and \( y_{g2} \) are inferred with the well-known method of the centre of gravity to obtain a fuzzy value \( f_y \) for each value of \( p_y \). For example, if \( p_y = \hat{g} \), then the gray level value of \( f_y \) in image \( I_f \) is given by:

\[
f_y = \frac{255}{2} \left( \frac{-y_{g1} + y_{g2}}{y_{g1} + y_{g2}} + 1 \right)
\]

where \( y_g = [y_{g1} \ y_{g2}] \). In this way, the histogram of \( I_f \) is emphasized toward the extreme values of gray levels with respect to image \( I \) and a contrast enhancement is achieved. A sparsely-connected \((4\times4)\)-cell Hopfield-type neural network, behaving as the just codified fuzzy procedure for contrast enhancement, can now be synthesized as in [9]. The implemented neural network behaves as a fuzzy system, able to enhance image contrast. The resulting image \( I_f \) presents a bimodal histogram, given by the discrete function:

\[
h_f(g) : g \rightarrow h_f \quad g = 0, 1, \ldots, 255
\]

being \( h_f \) = cardinality\{ \((i, j) \mid I_f(i, j) = g\) \}.

B. NN-based Threshold Computation

Contrast-enhanced images \( I_f \) present two-peak histograms [11]. The first peak concerns with information about deep areas in images \( I \), the other peak concerns with pale regions.
Retinal suspect areas can be highlighted in each contrast-enhanced image \( I_f \) by an adequate segmentation. For this purpose, an optimal thresholding computation is developed, by requiring that errors in classifying suspect regions be minimized. A NN-based subsystem formed by two Multi-Layer Perceptron networks MLP\(_D\) and MLP\(_P\) is designed for a globally optimal threshold computation as shown in Fig.2. For this purpose, let \( m \) denote the maximum gray level in \([1,254]\) such that \( h(m) \) is a relative minimum of histogram \( h(g) \). The following vectors can be defined:

\[
g = [1, 2, \ldots, 255]^T \in \mathbb{N}^{255x1} \\
h_0 = [h_1, \ldots, h_k, \ldots, h_m, 0, \ldots, 0]^T \in \mathbb{N}^{255x1} \\
h_p = [0, \ldots, 0, h_{m+1}, h_{m+2}, \ldots, h_{255}]^T \in \mathbb{N}^{255x1}
\]

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

\[
H_0 = [g, h_0] \in \mathbb{N}^{255x2} \\
H_p = [g, h_p] \in \mathbb{N}^{255x2}
\]

which contain information about deep areas and pale ones of contrast-enhanced images \( I_f \). Matrices \( H_0 \) and \( H_p \) provide proper sets for training each MLP network to recognize one mode of the bimodal histogram \( h(g) \) with one hidden layer. The globally optimal threshold, that minimizes errors in segmentation is given by the value \( T_h \) such that \([11]\)

\[
h_h(T_h) = h_p(T_h)
\]

It has to be said that the element \( h_0 \), containing the occurrences of black is discarded, because it contains almost only black pixels of image background.

Input layer and output one are each formed by one neuron with a logarithmic sigmoid transfer function. Such networks are characterized by one hidden layer, whose optimal number of neurons can be established by minimizing the Mean Maximum Error index (MME) both for MLP\(_D\) and MLP\(_P\):

\[
MME_D = \frac{1}{r} \sum_{i=1}^{r} \max \{ |h_p(g) - h(g)| / h(g) \}
\]

\[
MME_P = \frac{1}{r} \sum_{i=1}^{r} \max \{ |h_p(g) - h(g)| / h(g) \}
\]

and the Mean Percentage Error index (MPE) both for MLP\(_D\) and MLP\(_P\):

\[
MPE_D = \frac{100}{r} \sum_{i=1}^{r} \sum_{g=1}^{255} \frac{|h_p(g) - h(g)|}{h(g)}
\]

\[
MPE_P = \frac{100}{r} \sum_{i=1}^{r} \sum_{g=1}^{255} \frac{|h_p(g) - h(g)|}{h(g)} \quad g = 1, \ldots, 255
\]

being \( r \) the number of training phases carried out with different initial weights. Neural networks MLP\(_D\) and MLP\(_P\) behave as interpolators of histograms \( h_d(g) \) and \( h_p(g) \) by fitting discrete values of both modes which form histogram \( h(g) \). MLP neural networks are herein trained using four relevant training algorithms \([10]\) for a performance comparison:

- Gradient descent backpropagation (GDBP)
- Gradient descent momentum with adaptive leaning rate backpropagation (GD\(\mu\)BP)
- Conjugate gradient backpropagation with Fletcher-Reeves updates (CGFR)
- Levenberg-Marquardt backpropagation (LMBP)

C. Globally Optimal Segmentation

A globally optimum segmentation is the significant final step of the proposed intelligent system, since it generates output binary images which contain only significant information about suspect damaged retinal areas. As shown in \([11]\), errors in diabetic symptoms detection can be minimized if the globally optimal threshold \( T_h \), computed by the NN-based Threshold Computation block, is determined. Therefore, \( I_f \) can be segmented as follows

\[
I_b(i,j) = \begin{cases} 
255 & \text{if } I_f(i,j) < T_h \\
0 & \text{if } I_f(i,j) \geq T_h \end{cases} 
\]

where the bipolar image \( I_b \) provides a detailed mask, in which black pixels identify suspect areas in the original fundus image \( I \).

III. RESULTS

The capabilities of the proposed intelligent system have been investigated on a database of sixty (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.3 the green layer of a selected fundus image \( I \) and its histogram \( h(g) \) are reported. Diabetic symptoms given by vague pale regions can be noted in this image.
Several values of the fuzzy parameters $a \in [25, 50]$ and $b \in [60, 255]$, respectively, have been considered. Following the reported procedure, a $(4x4)$-neurofuzzy network has been implemented for $a=25$ and $b=200$ which give the least values of cited errors as discussed in the following. Fig.4 shows the evaluated contrast-enhanced image $I_f$ and its bimodal histogram obtained by processing the reported image $I$ with the designed neurofuzzy system. By considering that amounts of close pale pixels indicate suspect areas, the peak value equal to 4685 pixels in the histogram $h_f(g)$ summarizes bright damaged regions.

Table I - $MPE_D$ values versus the number of hidden neurons for selected learning algorithms

<table>
<thead>
<tr>
<th>Neurons in hidden layer</th>
<th>GDBP</th>
<th>GDX</th>
<th>CGBP</th>
<th>LMBP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11.086</td>
<td>9.9712</td>
<td>10.116</td>
<td>9.3799</td>
</tr>
<tr>
<td>2</td>
<td>12.179</td>
<td>13.003</td>
<td>8.8236</td>
<td>7.9209</td>
</tr>
<tr>
<td>3</td>
<td>13.638</td>
<td>8.1149</td>
<td>7.9016</td>
<td>7.8097</td>
</tr>
<tr>
<td>4</td>
<td>12.094</td>
<td>7.7392</td>
<td>7.6562</td>
<td>7.628</td>
</tr>
<tr>
<td>5</td>
<td>10.657</td>
<td>7.7158</td>
<td>7.6535</td>
<td>7.6163</td>
</tr>
<tr>
<td>6</td>
<td>12.476</td>
<td>7.7164</td>
<td>7.6374</td>
<td>7.5712</td>
</tr>
<tr>
<td>7</td>
<td>11.348</td>
<td>7.6546</td>
<td>7.6466</td>
<td>7.5854</td>
</tr>
<tr>
<td>8</td>
<td>10.195</td>
<td>7.6433</td>
<td>7.6332</td>
<td>7.485</td>
</tr>
<tr>
<td>9</td>
<td>10.41</td>
<td>7.644</td>
<td>7.6367</td>
<td>7.4381</td>
</tr>
<tr>
<td>10</td>
<td>10.583</td>
<td>7.6163</td>
<td>7.7561</td>
<td>7.8015</td>
</tr>
</tbody>
</table>

Table II - $MPE_P$ values versus the number of hidden neurons for selected learning algorithms

<table>
<thead>
<tr>
<th>Neurons in hidden layer</th>
<th>GDBP</th>
<th>GDX</th>
<th>CGBP</th>
<th>LMBP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.9533</td>
<td>8.1e-2</td>
<td>4.5e-2</td>
<td>1.9e-7</td>
</tr>
<tr>
<td>2</td>
<td>9.4821</td>
<td>7.4e-2</td>
<td>2.9e-2</td>
<td>3.6e-3</td>
</tr>
<tr>
<td>3</td>
<td>7.0497</td>
<td>6.1e-2</td>
<td>3.1e-2</td>
<td>3.6e-3</td>
</tr>
<tr>
<td>4</td>
<td>5.7965</td>
<td>5.5e-2</td>
<td>2.7e-2</td>
<td>5.0e-3</td>
</tr>
<tr>
<td>5</td>
<td>5.7004</td>
<td>5.5e-2</td>
<td>2.9e-2</td>
<td>3.6e-3</td>
</tr>
<tr>
<td>6</td>
<td>5.3155</td>
<td>4.9e-2</td>
<td>2.6e-2</td>
<td>2.9e-3</td>
</tr>
<tr>
<td>7</td>
<td>4.5289</td>
<td>5.3e-2</td>
<td>2.5e-2</td>
<td>1.4e-3</td>
</tr>
<tr>
<td>8</td>
<td>4.1201</td>
<td>4.7e-2</td>
<td>2.9e-2</td>
<td>2.1e-3</td>
</tr>
<tr>
<td>9</td>
<td>3.7138</td>
<td>4.6e-2</td>
<td>2.7e-2</td>
<td>7.3e-4</td>
</tr>
<tr>
<td>10</td>
<td>0.22273</td>
<td>4.2e-2</td>
<td>2.8e-2</td>
<td>9.4e-3</td>
</tr>
</tbody>
</table>

Due to the bimodal behaviour of the histogram $h_f(g)$, a globally optimal threshold computation has been successively performed [11] as reported in Section II-C. An optimal value $T_o = 207$ has been determined for segmenting image $I_f$. In Fig.5 the obtained binary output image $I_b$ is shown.

IV. DISCUSSION

The behaviour of the intelligent system has been analysed by determining the values of $MPE_D$ and $MPE_P$.
versus fuzzy parameters $a$, $b$. The values of fuzzy parameters $a$, $b$ to be adopted have been estimated by evaluating the least values of $MPE_D$ and $MPE_P$. In Fig. 6 the diagrams of the values of $MPE$ versus the fuzzy parameter $b$ are reported for $a \in [25, 50]$, both for MLP$_P$ and MLP$_D$. It can be noticed that the least values of $MPE$ are obtained when $b=200$ and $a=25$ for both networks.

![Fig. 6](image1)

Quality performances of the suggested intelligent system, have been evaluated by considering the so called gold standard image, provided by expert clinicians and shown in Fig. 7. For the sake of a better comparison, the image obtained by superimposing image $I_b$ to fundus image $I$ has also been reported in Fig. 7. In both images suspect diabetic areas are indicated with black pixels. 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 [2]. 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. Then, performances can be evaluated by computing the percentage value of the Correct Recognition Rate (CCR), defined as [12]:

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

In this paper pixels are classified as belonging to Suspect areas or Not Suspect ones. The value of $CCR\%$ has been computed by considering a (200x200) window centered on macula in image $I_b$ due to the fact that macula represents the fundamental fundus region from an ophthalmic point of view. Successively, this value has been compared to results obtained by the methods reported in [2] and in [5] as shown in Table III.

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>99.92</td>
<td>98.86</td>
<td>98.55</td>
</tr>
</tbody>
</table>

The proposed system provides a value of $CCR\% = 98.86$, being FP = 2395 and FN = 317. It can be observed that the
obtained $CCR\%$ is greater than the value computed using the method presented in [5]. Concerning with the $CCR\%$ value corresponding to Case A, it has to be pointed out that a further step of image processing was necessary to utilize the described procedure with respect to the proposed one. Thus, the method proposed in [2] gives a better $CCR\%$, but it seems more time-consuming. From this point of view, the value of $CCR\%=98.86$, herein evaluated for the presented system, can be considered as meaningful.

IV. CONCLUSIONS

In this paper, a contribution for improving the detection of diabetic symptoms has been presented by synthesizing an intelligent system for retinal image processing. A sparsely-connected Hopfield-type neural network has been firstly synthesized to behave as a fuzzy subsystem to enhance image contrast and highlight pale regions in fundus images of patients with diabetic pathologies. In this way, contrast-enhanced images with stretched histograms are computed, being particularly suitable for measurements of the gravity of diabetic symptoms. Then, a subsystem of two MLP neural networks has been trained selecting the Levenberg-Marquardt learning algorithm for evaluating the globally optimal threshold which can minimize pixel classification errors. Enhanced contrast images have been successively segmented, providing bipolar output images, in which suspect diabetic symptoms are isolated. The comparison between obtained images with gold standard ones provided by expert clinicians has successively revealed an improvement in detection of suspect diabetic areas by the presented system.

Quality performances of the proposed intelligent system have been finally evaluated and compared with results given in other studies by computing $CCR\%$ values.

Future work will concern with the development of automatic criteria for computing fuzzy parameters $a$ and $b$, on the basis of the evaluation of specific image features.

Further improvements of the proposed intelligent system are intended as a diagnostic support tool in diabetic patients’ follow up.

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REFERENCES