STUDIA INFORMATICA 2004
Volume 25 Number 1 (57)

Katarzyna STĄPOR, Michał MAZURKIEWICZ
Politechnika Śląska, Instytut Informatyki
Marek RZENDKOWSKI
Szpital Wielospecjalistyczny, Oddział Okulistyczny, Gliwice

NEURAL NETWORK CLASSIFICATION OF EYE-CUP REGION IN FUNDUS EYE IMAGES

Summary. In this paper the new method for classification of digital fundus eye images into normal and glaucomatous ones is proposed. The classifier used is based on multi-layer perceptron. The performance of the classifier is 94,77%. The obtained results are encouraging.

Keywords: neural network classification, backpropagation rule, glaucoma

KLASYFIKACJA NEURONOWA WNĘKI NACZYNIOWEJ NA CYFROWYCH OBRAZACH DNA OKA

Streszczenie. W artykule przedstawiono nowa metodę klasyfikacji obrazów dna oka uzyskiwanych z funduskamery na jaskrowe i zdrowe. W roli klasyfikatora zastosowano wielowarstwowy perceptron. Wyniki eksperymentu wykazały bardzo wysoką sprawność procedury klasyfikacyjnej: 94,77%. Otrzymane rezultaty są zachęcające.

Słowa kluczowe: klasyfikacja neuronowa, reguła propagacji wstecznej błędu, jaskra

1. Introduction

Glaucoma is a group of diseases characterized by the proceeding optic nerve neuropathy which leads to the rising diminution in vision field, ending with blindness. The correct eye disk structure contains *neuroretinal rim* of pink color placed on the *eye-disk* circuit and centrally placed yellowish *eye-cup* [6] (Fig. 1). Glaucomatous changes in retina appearance embrace various changes in neuroretinal rim and eye-cup, as the result of nerve fibers damages.

Fig. 1. The fundus eye image with the eye-cup area in the central part
Rys. 1. Obraz dna oka z wnęką naczyniową w centralnej części

The existing methods of qualitative analysis (i.e. based on ophthalmoscope and slit lamp with Volk lens) [6] are very subjective, while quantitative methods of eye-disc morphology evaluation (cup to disc ratio, neuroretinal rim area) do not result in full diagnosis. The new methods of morphologic analysis based on laser scanning ophtalmoscopy [6] are expensive and accessible only in specialized ophtalmic centres.

Thus, there is a need for better, cheaper and more objective methods of quantitative eye-disc structures evaluation which are based on methods of automatic analysis and recognition of digital images.

In [7] we proposed a new method for automatic segmentation of eye-cup region from fundus eye images acquired from standard fundus camera. Fig. 2 shows the automatically extracted eye cup region from sampled image shown in Fig. 1 by the segmentation method described in [7]. In [8] we proposed a new automatic feature selection method based on genetic algorithms for the purpose of eye-cup classification.

A successful eye-cup classification into normal and glaucomatous ones based on the suitable shape descriptors can boost the performance of applications supporting glaucoma diagnosing. Despite its importance, it has received no attention in the literature.

Fig. 2. The eye-cup segmented by the algorithm [7] from image shown in Figure 1
Rys. 2. Wnęka naczyniowa wysegmentowana algorytmem [7] z obrazu na rys. 1

In this paper we propose the new method for classification of digital fundus eye images (fei) into normal and glaucomatous ones. The classifier used is a multi-layer perceptron (MLP).

Fig. 3 shows all the stages of the proposed method for automatic analysis of fundus eye images which should support glaucoma diagnosing and monitoring process. This article describes the last stage – the classification procedure.

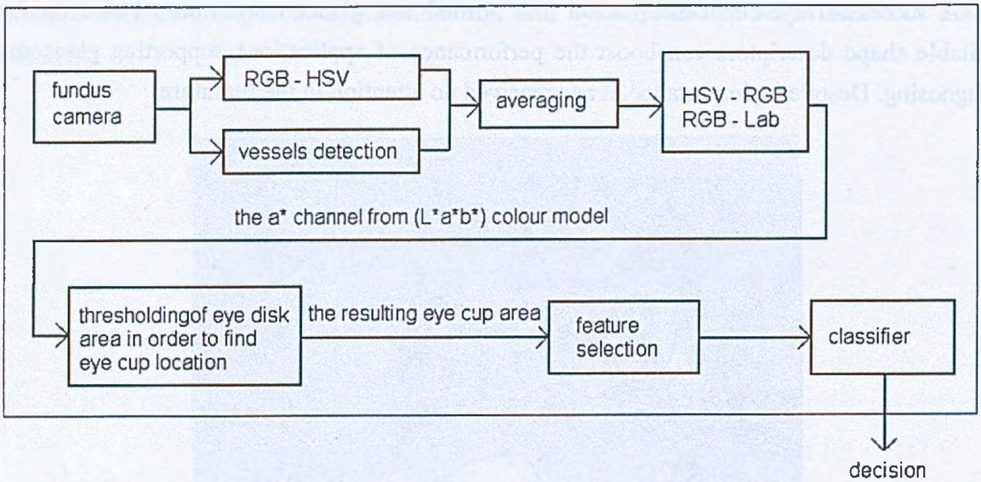

Fig. 3. Stages of the proposed method
Rys. 3. Etapy proponowanej metody

2. Feature selection

In [8] we determined what features played a significant role for the classification of eye-cup region. The eye-cup can be represented by the spatial central moments of order p+q (p, q are integers) of its intensity function [5,9]:

$$m_{pq} = \sum_{i=1}^{m} \sum_{j=1}^{n} (i-I)^p (j-J)^q \, p(i,j),$$

where $I = \frac{m_{10}}{m_{00}}$, $J = \frac{m_{01}}{m_{00}}$

and p(i,j) is the intensity function representing the image, mxn is the size of the image. Normalized central moments of order p+q are defined as:

$$\mu_{pq} = \frac{m_{pq}}{(m_{00})^{\alpha}} \qquad \alpha = \frac{p+q}{2} + 1$$

The following 8 features according to [8] compose a feature vector:

$$(\phi_3, I_1, I_2, I_5, I_7, I_{14}, R_{c2}, W_{SL})$$

One Hu moment invariant [9]:

$$\phi_3 = (\mu_{30} + 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2$$

Five from sixteen compound invariant moments [9]:

$$I_1 = \mu_{20}\mu_{02} - \mu_{11}^2$$

$$I_2 = (\mu_{30}\mu_{03} - \mu_{21}\mu_{12})^2 - 4(\mu_{30}\mu_{12} - \mu_{21}^2)(\mu_{21}\mu_{03} - \mu_{12}^2)$$

$$I_5 = \mu_{20} + \mu_{02}$$

$$I_7 = (\mu_{30} - 3\mu_{12})^2 + (\mu_{03} - 3\mu_{21})^2$$

$$I_{14} = \frac{I_4}{\mu_{00} I_2},$$

where:

$$I_4 = \mu_{30}^2\mu_{02}^3 - 6\mu_{30}\mu_{21}\mu_{11}\mu_{02}^2 + 6\mu_{30}\mu_{12}\mu_{02}(\mu_{11}^2 - \mu_{20}\mu_{02}) + \mu_{30}\mu_{03}(6\mu_{02}\mu_{11}\mu_{02} - 8\mu_{11}^3)$$
$$+ 9\mu_{21}^2\mu_{20}\mu_{02}^2 - 18\mu_{21}\mu_{12}\mu_{20}\mu_{11}\mu_{02} + 6\mu_{21}\mu_{03}\mu_{20}(2\mu_{11}^2 - \mu_{20}\mu_{02}) + 9\mu_{12}^2\mu_{20}^2\mu_{02}$$
$$- 6\mu_{12}\mu_{03}\mu_{11}\mu_{20}^2 + \mu_{03}^2\mu_{20}^3$$

One circular coefficient [9]:

$$R_{C2} = \frac{L}{\pi}$$

Area to perimeter coefficient:

W_{SL}=S/L

L – object perimeter

S – object area

3. The neural network classifier

The multi-layer perceptron (MLP) [1], also termed feed forwardnetwork, is a generalization of the single-layer perceptron studied by [3]. In fact, a feedforward neural network of just three layers (including the input layer) is enough to approximate any continuous function [2].

Supervised learning describes the case where the training data, measurements on the surroundings are accompanied by labels indicating the class of event that the measurement represent, or more generally the desired response to the measurements. In other words, in supervised learning, we have an instance of data *i* comprising an attribute vector x_i and a target vector d_i (i.e. a class):

$\{x_i, d_i\}$ for i=1,…,p

(p is the number of training examples).

The supervised learning network used in our experiment is the multi-layer perceptron.

Multilayer perceptron architecture

We process attribute vector x_i with a network to produce an output y_i, which has the same form as a target vector d_i.

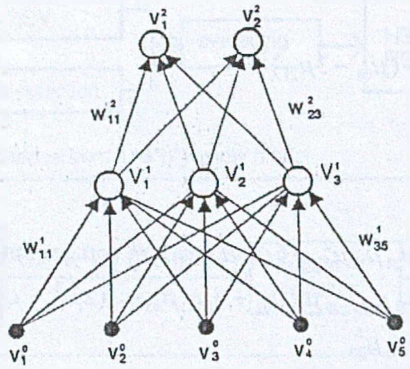

Fig. 4. The three-layer perceptron structure
Rys. 4. Perceptron 3-warstwowy

Fig. 4 shows the structure of a standard three-layer perceptron. The input nodes form the input layer of the network (nodes V_i^0). The outputs are taken from the output nodes (nodes V_i^2), forming the output layer. The middle layer of nodes (nodes V_i^1), visible to neither the inputs nor the outputs, is termed the hidden layer. The hidden layer is generally used to make a bottleneck, forcing the network to make a simple model of the system generating the data, with the ability to generalize to previously unseen patterns. The operation of this network is specified by:

$$V_j^1 = f^1\left(\sum_k w_{jk} V_k^0\right)$$

$$V_j^2 = f^2\left(\sum_k w_{jk} V_k^1\right)$$

This specifies how input pattern vector V_k^0 is mapped into output pattern vector V_k^2 via the hidden pattern vector V_k^1 in a manner parameterized by the two layers of weights: w_{ij}^1, w_{ij}^2. The univariate functions f^1 and f^2 are typically each set to:

$$f(x) = \frac{1}{1+e^{-x}}$$

Training

Training is the process of fitting network parameters (its weights w_{ij}) to given data. The training data consists of a set of examples of corresponding inputs x_i and desired outputs, or “targets” d_i.

The parameters of the network (i.e. weights) are modified during training to optimize the match between outputs and targets, typically by minimizing the total square error:

$$E(w) = \frac{1}{2}\sum_i (d_i - V_i^2)^2$$

In general, minimization is accomplished using a variant of gradient descent. This produces a local minimum of E(w) (w is a vector of weights w_{ij}). The calculation of gradient in MLP is conveniently organized as a backpropagation of error [1].

A backpropagation procedure for training three-layer MLP can be summarized in the following steps.

1. Initialize the weights w_{ij} as small random numbers, Set $\eta>0$, $E_{max}>0$, l=1, E=0
2. Apply an input vector $V_k^0 = x_k$ (k=1, ..., number of input nodes) to the network and forward propagate through the network:

   $$V_i^m = f(h_i^m) = f(\sum_j w_{ij}^m V_j^{m-1}) \quad (h_i^m = \sum_j w_{ij}^m V_j^{m-1})$$

   for each node i and each layer m (m=1,2 here) until all outputs V_i^2 are computed.
3. Evaluate errors δ_i for all nodes i in the output layer (m=2)

   $$\delta_i^2 = f'(h_i^2)[d_i - V_i^2]$$

4. Back-propagate the errors δ_j^2 on output layer to obtain δ_i^1 for each node i in a hidden layer:

   $$\delta_i^1 = f'(h_i^1)\sum_j w_{ji}^1 \delta_j^2$$

5. Update weights in both hidden and output layers:

   $$w_{ij}^{new} = w_{ij}^{old} + \Delta w_{ij}^m$$

   $$\Delta w_{ij}^m = \eta \delta_i^m V_j^{m-1} \quad m=1,2$$

6. Update cumulative error:

   $$E = E + \frac{1}{2}\sum_i [d_i - V_i^2]^2$$

7. If $l < p$ then $l = l+1$
8. If $E < E_{max}$ stop else goto 2

The trained network (classifier) can be used to determine which class of pattern in the training data each node or neuron in the network responds most strongly to, most frequently. Unseen data can then be classified according to the class label of the neuron with the strongest activation for each pattern. The neural network can directly construct highly non-linear decision boundaries, without estimating the probability distribution of the data.

Estimation the performance of the classifier – K-fold cross-validation method

We use K-fold cross validation procedure [4], where K=10, to evaluate the performance of the network. This procedure works as follows:

1. Split a data set of N instances into K cuts containing (N/K) random instances.
2. Form a testing set with each cut.
3. Form a training set for every testing set with the remaining (N-N/K) instances.
4. Train and test the neural network using each of the pair of training and testing sets.
5. Record and average the results for the testing sets to determine the performance of the network.

4. Experimental results and conclusions

The new method has been applied into 50 fei of patients with glaucoma which where previously examined by conventional methods (perimetry, slit lamp with Volk lens) and 50 fei of normal patients. On the acquired from Canon CF-60Uvi fundus camera images, the eye cup contour is automatically detected. Fig 1 shows the sampled fundus eye image, while Fig. 2 the resulted eye-cup region obtained using the segmentation method described in [7]. Genetic algorithms were then employed to select a subset of features (i.e. *pattern vectors*) from the obtained eye-cup region. The resulting 8-dimensional pattern vectors calculated on a 100 obtained eye-cup regions were the inputs to the MLP classifier.

We now briefly describe the architecture of the classifier used in our experiment. Fully connected 3-layer neural network shown in Fig. 3 was used in a classification procedure. The number of the neuron nodes in the first layer was chosen to be 8, corresponding to the dimensionality of the input pattern vectors. The 2 neurons in the third (output) layer correspond to the number of pattern classes, and the number of neurons in the middle layer was heuristically specified as 4. In the output layer, the two nodes from top to bottom represent classes w_i for i=1,2, respectively. After the network structure has been set, sigmoidal activation functions were selected in hidden and output layers. The learning rate η was equal to 1. Weights w_{ij} were initialized to the small random values from <-1,5, 1,5> interval and the network was trained by the described backpropagation algorithm on the set composed from the 100 pattern vectors obtained as described above. The output nodes were monitored during training. The network was said to have learned the shapes from the two classes when, for any training pattern from one class the output unit corresponding to that class had to be high (>0.95) while, simultaneously, the output of all other nodes had to be low (<0.05). The constructed classifier ran 5000 iterations to train and updated the weights each time training data were presented.

We use the described K-fold cross validation procedure, where K=10, to evaluate the performance of the network. Simulation results show that backpropagation attained mean recognition rate **94,77%.** The obtained results are encouraging. It is expected that the new method, after clinical tests would support glaucoma diagnosis based on digital fundus eye images obtained from funduscamera.

REFERENCES

1. Bishop C. M.: Neural networks for pattern recognition, Clarendon Press Oxford, 1995.
2. Blum E. K., Li L. K.: Approximation theory and feedforward networks, Neural Networks, v.4, nr 4, pp. 511-515, 1991.
3. Rosenblatt F.: The perceptron: a probabilistic model for information storage and organization in the brain. Psychological Review, v.65, pp. 386-408, 1958.
4. Devijver P. A., Kittler J.: Pattern recognition: a statistical approach, Prentice-Hall, 1982.
5. Gonzalez R. C, Woods R. E: Digital Image Processing. Prentice-Hall, 2002.
6. Kanski J. et al.: Glaucoma.A color manual of diagnosis and treatment. Butterworth-Heinemann, 1996.
7. Stąpor K., Pawlaczyk L., Rzendkowski M.: Adaptive local thresholding for automatic segmentation of eye-cup in fundus eye images. Studia Informatica, 2003, in press.
8. Stąpor K., Mazurkiewicz M., Rzendkowski M.: Genetic feature subset selection for eye-cup classification in fundus eye images. Studia Informatica, 2003, in press.
9. Trier O., Jain A., Taxt T.: Feature extraction methods for character recognition – a survey. Pattern Recognition, v.29, Nr 4, pp. 641-662, 1996.

Recenzent: Dr inż. Damian Bereska

Wpłynęło do Redakcji 23 lipca 2003 r.

Omówienie

W artykule przedstawiono nową metodę umożliwiającą klasyfikację cyfrowych obrazów dna oka uzyskanych z funduskamery na dwie klasy: normalnych osobników oraz chorych na jaskrę. Klasyfikacja opiera się na suboptymalnym wektorze cech wyznaczonym za pomocą algorytmów genetycznych. W roli klasyfikatora użyto wielowarstwowy perceptron z regułą propagacji wstecznej błędu. Wysoka sprawność klasyfikacji jest niezbędna dla zastosowania jej do wspomagania diagnozowania jaskry.

Na pozyskanych z funduskamery typu Canon CF-60Uvi obrazach dna oka zostaje wysegmentowany automatycznie obszar wnęki naczyniowej za pomocą metody zaproponowanej w [7]. Następnie za pomocą algorytmów genetycznych zostaje znaleziony suboptymalny wektor cech [8], który koduje tylko najważniejsze informacje o kształcie wnęki. Trójwarstwowy perceptron podlega procesowi uczenia za pomocą reguły propagacji wstecznej błędu. Testowanie nauczonego klasyfikatora wykazało sprawność 94,77%. Uzyskane rezultaty są zachęcające.

Adresses

Katarzyna STĄPOR: Politechnika Śląska, Instytut Informatyki, ul. Akademicka 16, 44-100 Gliwice, Polska, delta@ivp.iinf.polsl.gliwice.pl .
Michał MAZURKIEWICZ: Politechnika Śląska, Instytut Informatyki, ul. Akademicka 16, 44-100 Gliwice, Polska.
Marek RZENDKOWSKI: Szpital Wielospecjalistyczny, Oddział Okulistyczny, ul. Kościuszki, 44-100 Gliwice, Polska.