Automatic Detection of Glaucomatous Changes Using Adaptive Thresholding and Neural Networks

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Abstract. In this paper the new method for automatic classification of fundus eye images into normal and glaucomatous ones is proposed. The new, morphological features for quantitative cup evaluation are proposed based on genetic algorithms. For computation of these features the original method for automatic segmentation of the cup contour is proposed. The computed features are then used in classification procedure which is based on multilayer perceptron. The mean sensitivity is 90%, while the mean specificity: 86%. The obtained results are encouraging.

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 optic disk (i.e. the exit of the optic nerve from the eye known as "blind spot") structure contains: neuroretinal rim of pink color and centrally placed yellowish cup [6] (Fig. 2a). The cup is the area within the optic disc where no nerve fibers and blood vessels are present and in 3D image appears as an excavation. The neuroretinal rim is the area between optic disc border and cup border - see Fig. 2a. Glaucomatous changes in retina appearance embrace various changes in neuroretinal rim and cup, as the result of nerve fibers damages.

Optic disc structures evaluation is one of the most important examinations in glaucoma progress monitoring and diagnosis. Searching for glaucoma damages during routine examination is not an easy task and gives uncertain results even with the experienced ophthalmologist [6]. The existing methods of qualitative analysis are very subjective, while quantitative methods of optic disc morphology evaluation (cup to disc ratio, neuroretinal rim area) do not result in full diagnosis. The new methods of morphologic analysis based on scanning-laser-tomography are expensive and accessible only in specialized ophthalmic centers.

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In the existing approaches for supporting glaucoma diagnosing [4,7,8] the automatic extraction of the cup region from fei was not the area of interest. Also, automatic classification of single fei acquired from fundus cameras into normal and glaucomatous has received no attention.

That is why we have developed a more objective and cheaper method that enables automatic classification of digital fundus eye images (fei) into normal and glaucomatous ones. The fei images were obtained by classical fundus-camera. We plan to build the proposed methodology into classical fundus-camera software to be used in routine examinations by an ophthalmologist.

2 Methods

The proposed method for automatic detection of glaucomatous changes in fundus eye images is composed of the 3 main stages (shown in Fig. 1):

1. detection of the cup contour,
2. selection of the cup features using genetic algorithms,
3. classification of fundus eye images using neural network classifier

2.1 Automatic Detection of the Cup Contour

Digital fei are acquired from classical fundus camera in RGB additive color model [5]. The color normalization step using histogram specification [5] is performed to decrease the variation in the color of fei from different patients. A copy of the acquired fei is converted into HSV color model [5]. On RGB image blood vessels are detected automatically using a set of contour filters according to a method described in [3].

Based on the detected vessels, the averaging of H,S,V components in HSV image is performed to decrease the contrast. All pixels comprising the detected vessels lying inside the user rectangle belong to the subregion named here $R_{eyecup\_vessels}$. First, the input image is converted from RGB to HSV color model [5]. By overlying the image with detected vessels on the input, converted image all border pixels of the detected vessels are found (subregion $R_{eyecup\_vessels}$). For each border pixel in $R_{eyecup\_vessels}$ its new color components $[H_{avg},S_{avg},V_{avg}]$, being the average of the appropriate components of pixels lying in the 8-connected neighborhood outside of $R_{eyecup\_vessels}$ region are found. After recalculation of all border pixels, they are deleted, new border pixels are found and the process is repeated until size of $R_{eyecup\_vessels}$ is higher than 0.

This preprocessed HSV image is converted into L*a*b* color model [5]. For further examinations only channel a* is used. Next, the a* component of L*a*b* image is binarized by the proposed adaptive thresholding method which results in white pixels of the cup (i.e. the object) and black pixels of the rest of the image (i.e. the background). In the adaptive thresholding method a local threshold is found by statistically examining the intensity values of a local neighborhood of

each pixel. A window cantered at each pixel is constructed as its local neighborhood. The statistic used is a function:

$$T = M_{mean} - C, \tag{1}$$

where M_{mean} is a mean of gray level values in the window, C is a constans, experimentally set.

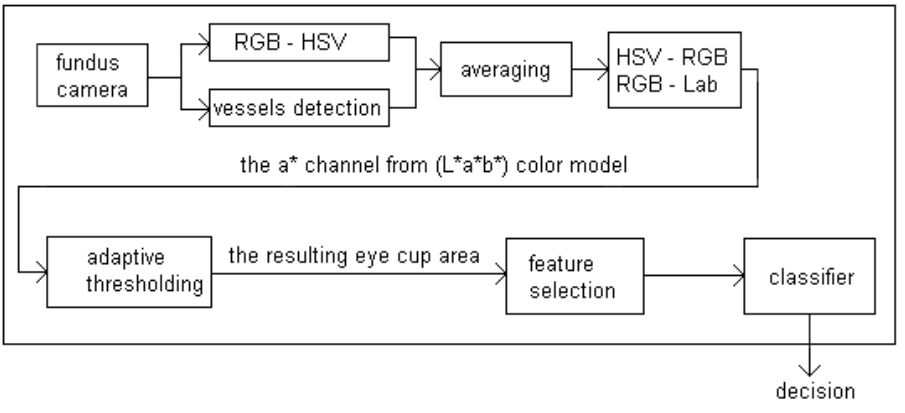
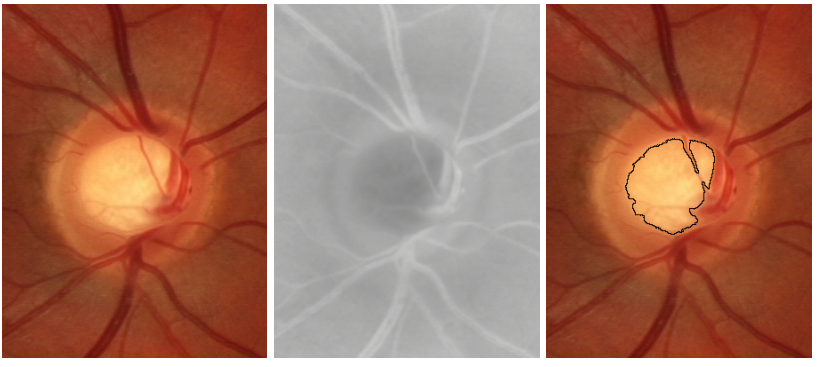


Fig. 1. Stages of the eye cup segmentation method

Due to nerve fibres damages during glaucoma progress, different changes in a shape of the neuroretinal rim (and of the cup) are observed. Proper shape feature selection can reduce not only the cost of recognition by reducing the number of features that need to be collected, but in some cases it can also provide a better classification accuracy due to finite sample size effect In our approach, 29 geometric features are computed on the extracted cup region. These are: seven Hu moment invariants [9], fifteen compound invariant moments [9], two circular coefficients [9], area to perimeter coefficient, Danielsson, Haralick, Blair-Bliss and Feret coefficients [9]. Genetic algorithms [1] are then used to select the most significant features characterizing the shape of cup region.

A given feature subset is represented as a binary string (a chromosome) of length n, with a zero or one in position i denoting the absence or presence of feature i in the set (n is the total number of available features). The initial population is generated in the following way: the number of 1's for each chromosome is generated randomly, then, the 1's are randomly scattered in the chromosome. A population of chromosomes is maintained. Each chromosome is evaluated to determine its "fitness", which determines how likely the chromosome is to survive and breed into next generation. We proposed the following fitness function:

$$Fitness = 10^4 accuracy + 0.4 zeros, \tag{2}$$



a) b) c)

Fig. 2. a) The initial image with the optic disk and the cup in the central part; b) channel a* of the input image; c) the contour of the extracted cup region overlaid on the input image

where accuracy is the accuracy rate that the given subset of features achieves (i.e. the performance of a classifier on a given subset of features), zeros is the number of zeros in the chromosome. Reproduction is based on a random choice according to a fraction with repetitions method [1]. New chromosomes are created from old chromosomes by the process of crossover and mutation [1].

The following 3 dimensional feature vector has been selected from a set of 29 features by genetic algorithm: (FI2, I3, RF), where

$$FI2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2, \tag{3}$$

is Hu invariant moment, where: η_{20}, η_{02}, η_{11} are normalized central moments. Normalized central moment of order (p+q) is defined as [5]:

$$\mu_{pq} = \frac{m_{pq}}{(m_{00})^{\alpha}}, \alpha = \frac{p+q}{2} + 1, \tag{4}$$

where: m_{pq} is a spatial central moment of order $p+q$ of an image f defined as:

$$m_{pq} = \sum_{i=1}^{m}\sum_{j=1}^{n}(i-I)^p(j-J)^q f(i,j), \tag{5}$$

$$I = \frac{m_{10}}{m_{00}}, \tag{6}$$

$$J = \frac{m_{01}}{m_{00}}, \tag{7}$$

$$I3 = \mu_{20}(\mu_{21}\mu_{03} - \mu_{12}^2) - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12}) + \mu_{02}(\mu_{30}\mu_{12} - \mu_{12}^2), \tag{8}$$

is compound, invariant moment.

$$R_F = \frac{L_h}{L_V} \tag{9}$$

is Feret coefficient, where:
L_h - maximal diameter in horizontal direction
L_V - maximal diameter in vertical direction.

2.2 Classification of Fundus Eye Images Using Neural Network Classifier

The method makes use of the 3-2-2 multilayer perceptron (MLP) [2]. The operation of MLP is specified by:

$$V_j^1 = f(\sum_k w_{jk} V_k^0), \tag{10}$$

$$V_j^2 = f(\sum_k w_{jk} V_k^1), \tag{11}$$

which 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 function f is set to:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{12}$$

The weights in the network are modified during training to optimize the match between outputs and targets d_i using standard backpropagation rule [2]:

$$w_{ij}^{m-new} = w_{ij}^{m-old} + \eta \delta_i^m V_{ij}^{m-1}, \tag{13}$$

where:

$$\delta_i^M = f'(\sum_j wi_{ij}^M V_j^{M-1})[d_i - V_i^M] \tag{14}$$

delta-error for i_{th} neuron in output layer M,

$$\delta_i^{m-1} = f'(\sum_j wi_{ij}^{m-1} V_j^{m-2}) \sum_j w_{ji}^m \delta j^m \tag{15}$$

$m = M, M-1, \ldots, 2$ delta-error for i_{th} neuron in hidden layer m. The trained network (classifier) can be used to determine which class of pattern in the training data each neuron in the network responds most strongly to. Unseen data can then be classified according to the class label of the neuron with the strongest activation for each pattern.

3 Results

The developed method has been applied into 100 fei of patients with glaucoma and 100 fei of normal patients which where previously examined by conventional methods by ophthalmologist. On the acquired from Canon CF-60Uvi funduscamera images, the cup contour is automatically detected. Next, for the detected

cup the whole set of 29 geometric features is computed. The obtained set of labeled feature vectors is divided into 4 parts: two training and two testing sets. One pair composed of one training and one testing set is used by genetic algorithms for suboptimal feature vector calculation, while the second pair of sets for calculation of a performance of neural network classifier.

The parameters of genetic algorithm used in all experiments are as follows: the length of each chromosome is 29 (equal to the number of features), population size is 120. Genetic algorithm converged to the final solution after 150 generations.

The parameters of a neural network classifier are as follows: the structure is set as 3-2-2 as described above, sigmoidal function is used as activation functions in hidden and output layers. The learning rate η is equal to 1. Weights w_{ij} are initialized to the small random values from $(-1.5, 1.5)$ interval. Classifier performance is tested by k-fold cross validation method. During performance evaluation, the constructed classifier ran 5000 iterations to train and updated the weights each time training data were presented. The following mean results has been obtained: sensitivity 90% and specificity 86%.

4 Conclusions

As far as we know no automatic method for the segmentation and classification of fei acquired from fundus-cameras into normal and glaucomatous has been reported yet. Our method proves that shape of the cup and its numerical characteristics correlate with progress of glaucoma. It also shows that by reducing irrelevant information and using only selected features the classifier performance can be improved significantly which is very important for application supporting glaucoma diagnosing.

The obtained results are encouraging. It is expected that the new method, after clinical tests would support glaucoma diagnosis based on digital fei obtained from fundus-camera.

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