STUDIA INFORMATICA 2004
Volume 25 Number 3 (59)

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AUTOMATIC SEGMENTATION OF FUNDUS EYE IMAGES USING FUZZY CLUSTERING FOR SUPPORTING GLAUCOMA DIAGNOSING

Summary. In this paper the new method for automatic segmentation of cup region from fundus eye images taken from classical fundus camera. The proposed method which is based on fuzzy clustering algorithm is a first step in automatic classification of fundus eye images into normal and glaucomatous ones.

Keywords: image segmentation, fuzzy clustering, glaucoma.

AUTOMATYCZNA SEGMENTACJA OBRAZÓW DNA OKA Z WYKORZYSTANIEM KLASTERYZACJI ROZMYTEJ DLA WSPOMAGANIA DIAGNOZOWANIA JASKRY

Streszczenie. W artykule przedstawiono nową metodę automatycznej segmentacji wnęki naczyniowej na cyfrowych obrazach dna oka. Metoda wykorzystuje klasteryzację rozmytą i stanowi pierwszy etap w systemie automatycznej klasyfikacji obrazów dna oka na jaskrowe i normalne.

Słowa kluczowe: segmentacja obrazu, klasteryzacja rozmyta, jaskra.

1. Introduction

Glaucoma is a group of ocular 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 (Fig. 1).

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. Glaucomatous changes in retina appearance embrace various changes in neuroretinal rim and cup, as the result of nerve fibers damages.

Fig. 1. The input fundus eye image
Rys. 1. Wejściowy obraz dna oka

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 analysis based on scanning-laser-tomography are expensive and accessible only in specialized ophthalmic centers.

In the existing approaches to automatic segmentation of fundus eye images for supporting glaucoma examinations [3,7,8,9] researchers focused on the detection of the optic disk and its characteristics. Typical methods of finding optic disk boundary are: active contour model (snakes), arc fitting to optic disk boundary using error minimization, Hough transform.

In this paper the new automatic segmentation method of the cup from fundus eye images is presented. The novelty relies on the automatic segmentation of the cup from fundus eye images, which wasn't the area of interest in the past. The proposed method relies on the fact that shape of the cup and its numerical characteristics correlate with progress of glaucoma. The next step will be a classification of digital **fundus eye images** (**fei**) into normal and glaucomatous ones based on the suitable shape descriptors which is the subject of our current work.

The Authors would like to thank prof. George Michelson from Department of Ophthalmology, Friedrich-Alexander-University Erlangen-Nuremberg for the possibility to access a database with fundus eye images, as well as for medical consultation.

2. Segmentation of the cup region

Image segmentation is a method to partition image pixels into similar regions. The clustering methods divide a set of N observations $x_1,...,x_N$ (data vectors) into c groups (clusters) denoted $\Omega_1,...,\Omega_c$, so that members of the same group are more similar to one another than to members of other groups [1, 4 ,5]. In this section we propose the new cup segmentation method from fei based on clustering in an image feature space. However, fei, like most medical images always present overlapping gray-scale intensities for different parts. In particular, borders between anatomical parts of fei are not clearly defined and memberships in the boundary regions are intrinsically fuzzy. The conventional, hard clustering methods restrict each point of the data set to exactly one cluster. Fuzzy sets give the idea of uncertainty of belonging described by a membership function [1]. In this case the membership degree of a vector x_k to the i-th cluster (u_{ik}) is a value from [0,1] interval. Therefore, fuzzy clustering methods are particularly suitable for the segmentation of medical images.

The proposed cup segmentation method relies on one of the most popular fuzzy clustering methods – the fuzzy c-means [1, 2].

2.1. The fuzzy c-means method

In fuzzy clustering methods, the set of all possible fuzzy partitions of N, p-dimensional vectors into c clusters (the so-called *c-partition matrices*) is defined by:

$$M_{fcN} = \left\{ U \in M_{cN} \,\middle|\, \underset{\substack{1 \le i \le c \\ 1 \le k \le N}}{\forall} 1)\ u_{ik} \in [0,1],\ 2)\ \sum_{i=1}^{c} u_{ik} = 1,\ 3)\ 0 < \sum_{k=1}^{N} u_{ik} < N \right\} \tag{1}$$

M_{cN} a space of all real (cxN)-dimensional matrices

The fuzzy c-means criterion function has the form:

$$J_m(U,V) = \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m d_{ik}^2 \tag{2}$$

where:

$U \in M_{fcN}$

$V = [v_1 .... v_c] \in M_{pc}$ prototypes (cluster centers) matrix

$m \in [1, +\infty]$ weighting component

d_{ik} the inner product induced norm:

$$d_{ik}^2 = \| x_k - v_i \|_A^2 = (x_k - v_i)^T A (x_k - v_i) \tag{3}$$

A positive-definite matrix

The **fuzzy c-means** method (**FCM**) [1,2] is based on minimization of the criterion function (2). This can be accomplished using the algorithm given below.

1. Fix the number of clusters c, $1<c<N$, where N is the number of data vectors. Fix m, the weighting component, $m \in [1, +\infty]$. Choose any inner product induced norm metric $\|.\|$. Choose ε, the convergence threshold. Set $j=0$.
2. Initialize the fuzzy c-partition matrix, U^0.
3. Calculate the c cluster centers $V^{(j)} = [v_1^{(j)}, ..., v_c^{(j)}]$ with $U^{(j)}$ using the formula:

$$\underset{1 \le i \le c}{\forall} \quad v_i = \left[\sum_{k=1}^{N} (u_{ik})^m x_k \right] \Bigg/ \left[\sum_{k=1}^{N} (u_{ik})^m \right]$$

4. Update fuzzy c-partition matrix $U^{(j+1)}$ for $(j+1)$ in j-th iteration iteration as follows:

   a) For each data item k calculate the sets: I_k and $\tilde{I}_k$:

$$\underset{1 \le k \le N}{\forall} \begin{cases} I_k = \{ i \mid 1 \le i \le c; d_{ik} = 0 \} \\ \tilde{I}_k = \{1, ..., c\} \setminus I_k \end{cases}$$

   b) For each data item k compute new membership values:

$$\underset{\substack{1 \le i \le c \\ 1 \le k \le N}}{\forall} \quad u_{ik} = \begin{cases} \underset{i \in \tilde{I}_k}{\forall} \; 0 \quad \sum_{i \in I_k} u_{ik} = 1 & I_k \ne \varnothing \\ \left(\dfrac{1}{d_{ik}} \right)^{\frac{2}{m-1}} \Bigg/ \left[\sum_{j=1}^{c} \left(\dfrac{1}{d_{jk}} \right)^{\frac{2}{m-1}} \right] & I_k = \varnothing \end{cases}$$

5. Compare $U^{(j)}$ and $U^{(j+1)}$ in a convenient matrix norm:
   if $\| U^{(j+1)} - U^{(j)} \| > \varepsilon$, then set $j=j+1$, goto step 3
   else stop.

2.2. Fuzzy clustering segmentation

Having compared several color spaces, we found the contours of the cup region to appear most continuous and most contrasted against the background in the *a* channel of the *Lab* color space [4] which can be computed as:

$$a = 50\left[\sqrt[3]{\frac{X}{X_o}} - \sqrt[3]{\frac{Y}{Y_o}}\right]$$

The values of X, Y can be computed by a linear transformation from (R,G,B) tristimulus coordinates [4]:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.607 & 0.174 & 0.200 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 1.116 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

and (X_0, Y_0) are *(X,Y)* values for standard white.

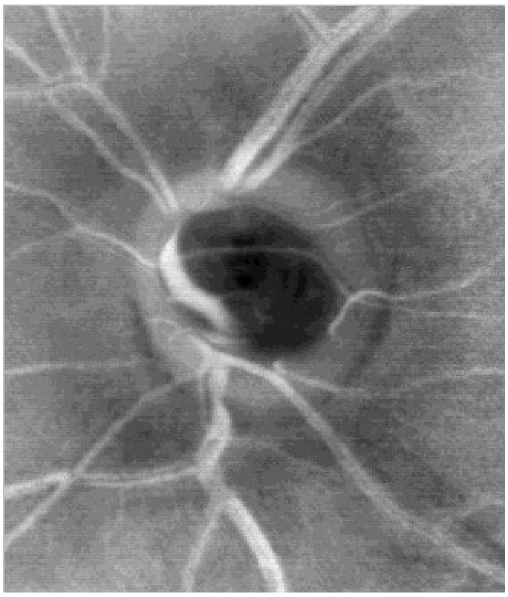


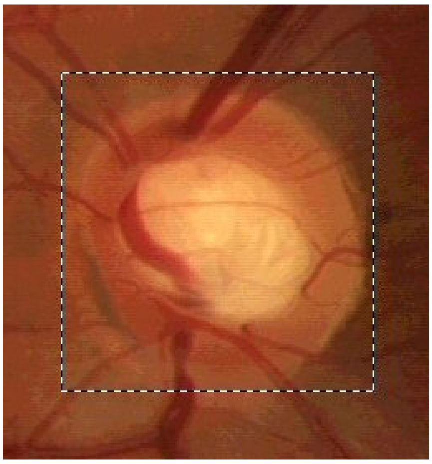
Fig. 2. Channel *a* of Lab color model of the image shown in Fig.1
Rys. 2. Kanał *a* w modelu Lab obrazu pokazanego na rys.1

From experiments we determined that applying the clustering algorithms to the full size image with a large number of pixels results in excessively long processing time. Therefore, we would use window segmentation to extract cup region: before the algorithm starts a user is asked to indicate a rectangle, which contains the optic disk (see Fig.3a).

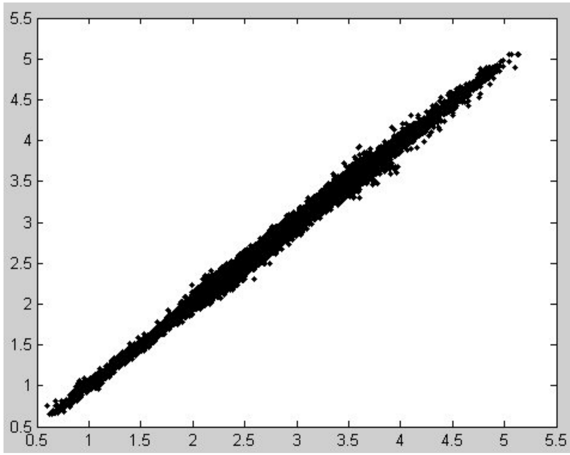
The FCM algorithm requires choosing the appropriate attribute information to perform the clustering task. The vector composed of the following two attributes has been considered for describing each pixel in an image:

(*value of channel a in Lab model*, *the most frequent value in 5x5 pixel neighborhood*)

The set of computed feature vectors (i.e. the set of data vectors to cluster) for the images available in our experiment (composed of the training and testing examples) is shown in Fig 3b).



a)



b)

Fig. 3. Fundus eye image from Fig.1: a) with the window selected, b) the set of feature vectors for pixels in a window (space for clustering)

Rys. 3. Obraz z rys. 1: a) z wybranym oknem, b) zbiór wektorów cech dla pikseli w oknie

The clusters were reduced into four types (c=4): optic disc, cup region, retina and blood vessels. The initialization of 4-partition matrix U^0 is done in the following way. Each feature vector is initially placed into one of the 4 clusters based on the value of channel *a*, i.e. depending into which of the four sections of equal length between a_{min} and a_{max} that value a falls in (a_{min} and a_{max} are minimum and maximum values of channel a of all pixels comprised in a window). The FCM algorithm is developed by considering $m=2$, the following matrix norm:

$$\| U^{l+1} - U^{l} \| = \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik}^{l+1} - u_{ik}^{l})^2$$

and the convergence threshold $\varepsilon = 0.01$

The output of the clustering algorithm gives a matrix U containing the fuzzy memberships associated to each of the four fuzzy regions considered. To obtain a cup region it is necessary to defuzzify the obtained fuzzy c-partition matrix which is accomplished in the following way: (h denotes hard while f fuzzy c-partition matrices)

$$u_{ik}^{h} = \left\{ 1 \quad \max_{1 \le p \le c} u_{pk}^{f} = u_{ik}^{f} \right\}$$

Figures 4-6 show the membership function produced by the described FCM algorithm for the window image shown in Fig.3a, the result of the segmentation obtained from this memberhip function, and finally, the contours of the cup region superimposed on the input image, respectively.

Fig. 4. Fuzzy membership function for the cup region
Rys. 4. Rozmyta funkcja przynależności dla wnęki

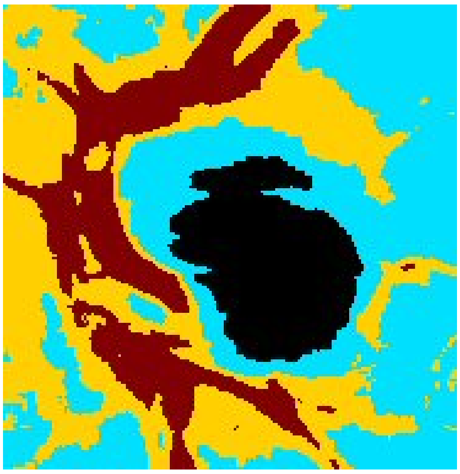


Fig. 5. Segmentation obtained from the fuzzy membership function after defuzzification
Rys. 5. Wyniki segmentacji z funkcji przynależności po defuzyfikacji

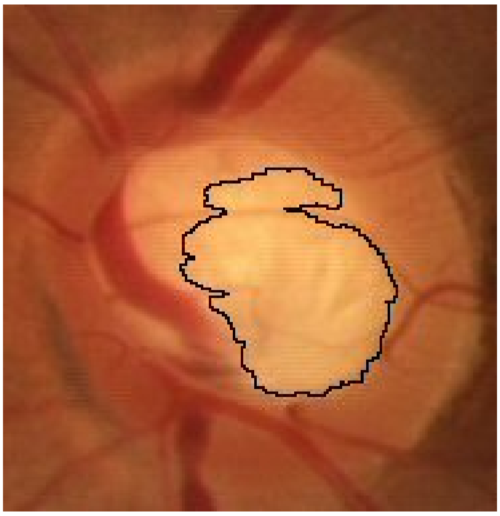


Fig. 6. The contour of the extracted cup region superimposed on the input image
Rys. 6. Kontur wysegmentowanej wnęki nałożony na obraz wejściowy

3. Results

The developed method has been applied into 50 fei of patients with glaucoma and 50 fei of normal patients which where previously examined by conventional methods by an ophthalmologist. On the acquired from Canon CF-60Uvi fundus-camera images, the cup contour is automatically detected by the segmentation method described in section 2. Fig. 6 shows the contour of the cup region segmented from the exampled fundus eye image shown in Fig.1. Figures 4 and 5 show the results of the successive stages of the presented segmentation method.

It is important to note that contours of the cup obtained as a result of the presented segmentation method coincide with the contour marked by an ophthalmologist. The results of using the presented method are very encouraging.

The feature extraction of the suitable cup shape descriptors, as well as the classification of the segmented fundus eye images into normal and glaucomatous ones are now being developed.

4. Conclusions

In this work we demonstrated the new method for the detection of the glaucomatous changes (i.e. a shape of a cup region) from fundus eye images in opthalmology. As far as we know, no automatic method for the segmentation of fei acquired from fundus-cameras has been reported yet. The proposed segmentation method is a first step in a system for automatic classification of fei for supporting glaucoma diagnosis.

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Recenzent: Dr inż. Krzysztof Fujarewicz

Wpłynęło do Redakcji 31 marca 2004 r.

Omówienie

W artykule przedstawiono nową metodę automatycznej segmentacji wnęki naczyniowej na cyfrowych obrazach dna oka pozyskanych z klasycznej funduskamery. Opracowana metoda segmentacji wykorzystuje algorytm klasteryzacji rozmytej FCM [1]. Algorytm wykorzystuje kanał *a* modelu Lab [4] obrazu wejściowego. Zastosowano 2-wymiarową przestrzeń cech do klasteryzacji złożoną z następujących dwóch atrybutów: 1) wartość kanału *a* modelu kolorów Lab oraz 2) wartość kanału *a* najczęściej występującą w sąsiedztwie piksela o rozmiarze 5x5. Klasteryzację, po zastosowaniu inicjalizacji, ustaleniu pozostałych parametrów wykonano dla liczby klasterów 4: dysk optyczny, wnęka naczyniowa, siatkówka oraz naczynia krwionośne. Rysunek 1 pokazuje przykład konturu wnęki naczyniowej uzyskany za pomocą opisanej metody, nałożony na wejściowy obraz dna oka. Opracowana metoda stanowi pierwszy etap w systemie automatycznej klasyfikacji obrazów dna oka na jaskrowe i normalne.

Adresy

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