Fundus Images Segmentation by Unsupervised Classification

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Abstract

In this paper, we present an original unsupervised segmentation scheme which splits a grey level image into different sets of connected pixels whose grey levels are homogeneous. This approach is based on an analysis of a triangular table denoted "Normalized connectivity degrees pyramid". This method is used in order to detect cytomegalovirus retinitis lesions by fundus image analysis. First, we determine the number of pixels classes and their cores. The core of each class C_j is represented by an interval of grey levels $[min_{C_j}, max_{C_j}]$. For classification purpose, the pixels whose grey level belongs to such an interval are labelled to the corresponding class. The other pixels are assigned by comparison of their conditional probability to belong to the different classes.

1 Introduction

A retinal lesion called CytoMegaloVirus (CMV) retinitis was found for patients suffering from immune deficiency syndrome (AIDS). The patients may lose their visual capability because this ocular infection attacks the optic nerve, the papilla, blood vessels, and the fovea, involving a progressive retinal destruction. The ophthalmologists have to evaluate the evolution of the lesion surface and the color of the retinal in order to determine the response of the CMV retinitis to antiviral therapy.

The evolution of these lesions is evaluated by ophthalmologists through a visual examination of serial fundus photographies where these lesions appear as textured yellow regions against a red background.

As it is difficult to distinguish the contours of these yellow regions, the ophthalmologists can't achieve accurate and reliable measures.

Such limitations call for an automatic system in order to process colorimetric and geometrical information of the retinitis lesions by color fundus images analysis. Such a system will be designed in order to evaluate the evolution of a lesion by the comparison of successive fundus images.

In this paper, we present a new image segmentation scheme designed to extract the homogeneous regions which represent the retinitis lesions from grey level fundus images.

The segmentation is achieved by an unsupervised pixels classification scheme in which an homogeneous region is a set of connected pixels which are assigned to the same class characterized by the grey levels of its pixels.

In order to segment biomedical images, Cheng and al. [1] propose a segmentation method using a competitive hopfield neural network based upon the global grey levels distribution. Vitulano and al. [2] propose a hierarchical tree approach (e.g. quad-tree). The relation between the entropy of an image and the entropy of its sub-domains is explored as an uniformity predicate. Recently, another developed approach consists in applying the concept of fuzzy objects in order to detect multiple sclerosis lesions [3]. An operator interactively selects a few points in the image by pointing different objects in the scene. Then, each of these objects is modelized as a fuzzy connected set. The holes in the union of these objects correspond to potential lesions sites. The weakness of this lesions detection system is a high computational cost. Dealing with detection of bright lesions on eye fundus images, Goldbaum and al. [4] propose to convolute a flat circular bright object template at multiple scales to detect potential bright lesions. The border of the gross lesions are refined by an histogram thresholding technique.

Among the literature, dealing with image segmentation, some papers privilege either the photometric properties of the pixels [5, 6] or their spatial properties [7].

Our method analyses simultaneously the photometric and the spatial pixels properties, in order to determine the number of classes in a pixel population and their core. The photometric and spatial pixels properties are merged into a new concept : the "normalized connectivity degrees pyramid".

The connectivity concepts which are presented in the second section of this paper, are used to define a new representation of the connectivity properties of an image: the normalized connectivity degrees pyramid, denoted $NCDP$, which is presented in the third section.

Then, in the fourth section, we explain the classification scheme which is based on the analysis of this pyramid. We explain how the pixels are assigned to the different classes which represent the homogeneous regions in the image.

In the last part, we show how this approach is applied with success to the segmentation of fundus images in order to extract retinitis lesions.

2 Connectivity notions

2.1 Connectivity of a pixel with a set of pixels $\mathbf{S[k,l]}$

Let $P(x,y)$ be the pixel with spatial coordinates (x,y), whose grey level is $g(x,y)$, $g(x,y) \in [0,1,...,N-1]$. Let $V(x,y)$ be the set of pixels that belong to the 8-neighborhood of $P(x,y)$ and $S[k,l]$ the set of pixels whose grey levels lie between level k and level l, with $0 \leq k \leq N-1$ and $0 \leq l \leq N-1$. The connectivity of $P(x,y)$ with $S[k,l]$, denoted $C_{S[k,l]}(x,y)$, is the number of pixels which belong simultaneously to $S[k,l]$ and $V(x,y)$ (see fig. 1) :

$$C_{S[k,l]}(x,y) = Card\{P(i,j) \in V(x,y) \mid P(i,j) \in S[k,l]\} \quad (1)$$

$0 \leq C_{S[k,l]}(x,y) \leq 8$

5	3	3
5	$P(x,y)$	8
5	7	4

$C_{S[3,4]}(x,y) = 3$, $C_{S[3,8]}(x,y) = 8$.

Figure 1: Examples of connectivity

2.2 Connectivity degree of a set of pixels $\mathbf{S[k,l]}$

We define the connectivity degree as :

$$CD(S[k,l]) = \frac{1}{CardS[k,l]} \sum_{P(x,y) \in S[k,l]} C_{S[k,l]}(x,y) \quad (2)$$

It represents the mean value of the connectivity with $S[k,l]$ of the pixels which belong to the set $S[k,l]$. A connectivity degree standing close to eight indicates that most of the pixels which belong to the set are connected. On the other hand, a low connectivity degree, close to zero, means that the pixels which belong to $S[k,l]$ are scattered in the image.

2.3 Normalized connectivity degree of a set of pixels $\mathbf{S[k,l]}$

The connectivity degree of a set depends on the size of the grey level interval $[k,l]$ but doesn't take into account the dispersion of the grey levels of its pixels. That leads us to define a normalized connectivity degree of a set by its variance, in order to obtain a measure of its connectivity which is sensitive to its grey levels dispersion.

We define the normalized connectivity degree as :

$$NCD(S[k,l]) = \frac{DC(S[k,l])}{1 + var(k,l)} \quad (3)$$

for an image coded on N grey levels, with :

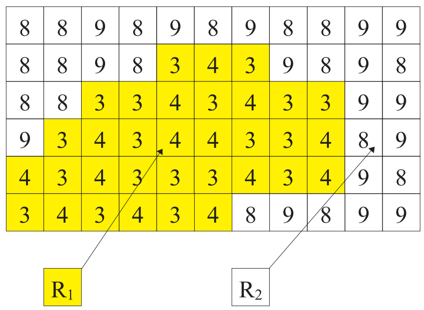
$$moy(k,l) = \frac{1}{CardS[k,l]} \sum_{P(x,y) \in S[k,l]} g(x,y) \quad (4)$$

and :

$$var(k,l) = \frac{1}{CardS[k,l]} \sum_{P(x,y) \in S[k,l]} (g(x,y) - moy(k,l))^2 \quad (5)$$

Let us consider fig. 2, which represents an image which contains two regions :

- R_1 composed of pixels with grey levels that belong to the interval $[3,4]$,
- R_2 composed of pixels with grey levels that belong to the interval $[8,9]$.



$$CD(S[3,9]) > CD(S[3,4]) \text{ and}$$
$$CD(S[3,9]) > CD(S[8,9])$$

$$NCD(S[3,4]) > NCD(S[3,9]) \text{ and}$$
$$NCD(S[8,9]) > NCD(S[3,9])$$

Figure 2: Example of connectivity degrees and normalized connectivity degrees

The connectivity degree of $S[3,9]$ is greater than the connectivity of $S[3,4]$ and the connectivity of $S[8,9]$. The reason isn't that the region, formed by pixels of $S[3,9]$, is more homogeneous than the pixels of $S[3,4]$. That's because $S[3,4]$ is included in $S[3,9]$. If we want to distinguish R_1 from R_2, we have to compare of the normalized connectivity degrees.

As these degrees are normalized by the variance of the grey levels, $NCD[3,4]$ and $NCD[8,9]$ are greater than $NCD[3,9]$.

In conclusion, this case illustrates that the normalized connectivity degree seems to be an interesting measure of the connectivity of a set of pixels.

3 Normalized connectivity degrees pyramid

The normalized connectivity degree is a good measure in order to determine the sets of pixels which represent homogeneous regions in an image. So, it is interesting to detect the higher normalized connectivity degrees. For this purpose, we introduce a new representation concept of connectivity properties: the normalized connectivity degrees pyramid $NCDP$.

This $NCDP$ is a triangular table which is composed of N superposed lines which are identified by their number p, $p = 1, ..., N-1$. N is the number of grey levels. A line number p contains $N-p$ cells. k is the horizontal rank in the pyramid with $k = 0, ..., N-p-1$ so that the cell on the line number p of rank k is denoted $T_{k,p}$.

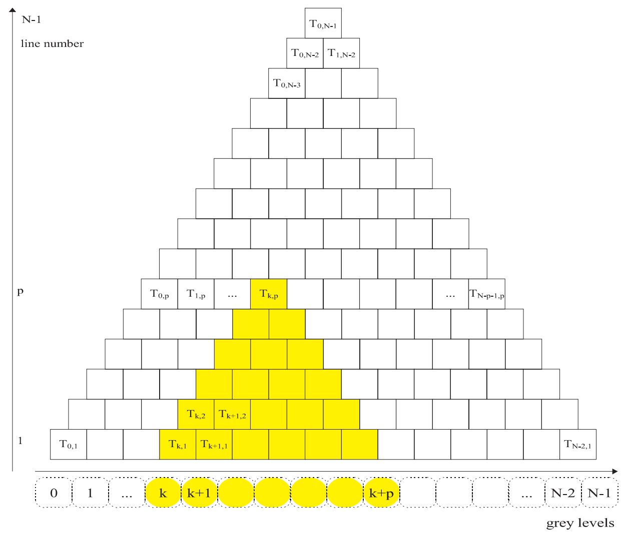


Figure 3: Normalized connectivity degrees pyramid

The cell $T_{k,p}$ contains the normalized connectivity degree of the pixels whose the grey levels are between k and $k+p$. (see fig. 3).

$$T_{k,p} = NCD(S[k, k+p]) = NCD(\{S(k) \cup S(k+1) \cup ... \cup S(k+p)\}) \quad (6)$$

The base line of the pyramid, i.e. line number 1, contains $N-1$ cells $T_{k,1}$ which correspond to the normalized connectivity degrees of $S[k, k+1]$ with $k = 0, ..., N-2$. The line p, contains $N-p$ cells $T_{k,p}$ which correspond to the normalized connectivity degrees of $S[k, k+p]$ with $k = 0, ..., N-p-1$.

4 Pixels classification

4.1 Introduction

A pixel classification scheme, based on the analysis of the $NCDP$, is proposed, which is divided into two steps.

First, we analyze the pyramid in order to evaluate the number of classes and their cores. We suppose that a core of a class C_j is the set of prototypes pixels of the class C_j, $S[min_{C_j}, max_{C_j}]$. So the pixels whose grey levels are in $[min_{C_j}, max_{C_j}]$ constitute the core of C_j.

Then, each class is examined a second time in order to decide if it must be split into different classes of pixels.

When the classes are determined, the pixels of the image are labelled.

4.2 Evaluation of the number of classes and their core

The analysis of the normalized connectivity degrees pyramid is achieved line by line, from the base line, i.e. line number 1, to the top, i.e. the line $N-1$. The line number p of the pyramid contains $N-p$ cells, $T_{k,p}$, which represent the normalized connectivity degrees of sets of pixels. These $N-p$ degrees form a series of discrete values with local maximums and minimums from which it is possible to extract some features (see fig. 4).

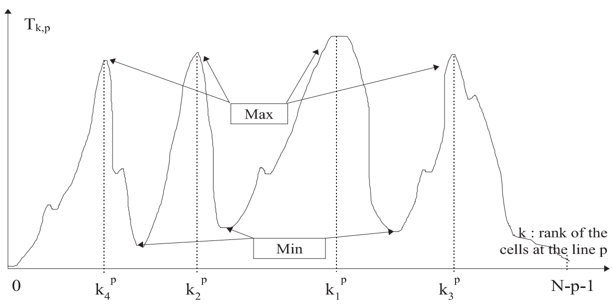


Figure 4: A series of discrete values $T_{k,p}$

Let suppose that $T_{k_1,p}$ is the maximum value of $T_{k,p}$, $k=0,1,...,N-p-1$. It corresponds to the top of an hill. That means that the set $S[k_1,k_1+p]$ is the set of pixels among the $N-p$ possible sets, which form the more homogeneous region in the image. So, in order to determine the classes of pixels, we propose to detect the local maximums of the series $T_{k,p}$. To each local maximum of this series, is associated a candidate class of line number p.

The detection of the local maximums is achieved by a MAX-MIN algorithm which is detailed in [8].

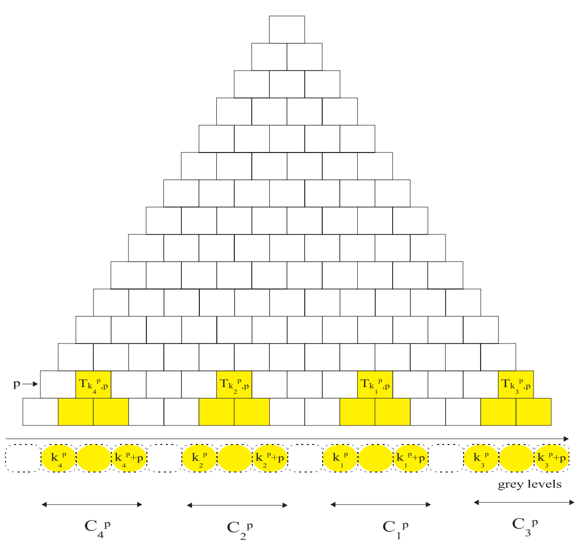


Figure 5: Pyramid which corresponds to fig. 4

The analysis of each line p generates a number of candidate classes denoted $NC(p)$ with $0 \leq NC(p) \leq (N-p)/2$. Let $T_{k_j^p,p}$, $j=1,2,...,NC(p)$, $0 \leq k_j^p \leq N-p-1$ denote the $NC(p)$ local maximums of the line number p. Each candidate class C_j^p has a core $S[k_j^p, k_j^p+p]$. (see fig. 4 and 5). Now, we explain how we select the line number p_0 for which we consider that $NC(p_0)$ is the actual number of classes.

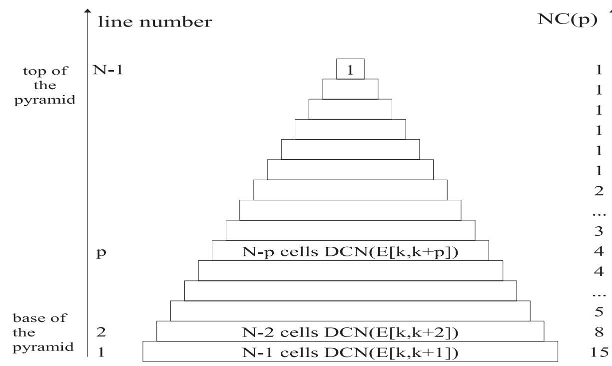


Figure 6: Number of candidate classes

Experiments shows that the number of candidate classes varies significantly from line to line at the bottom of the pyramid while it becomes more and more stable as we move towards the top of the pyramid. Furthermore, the higher we consider the line in the pyramid, the lower the number of candidate classes is, and consequently the higher the cardinal of such classes is. When we consider a line close to the top of the pyramid, the number of candidate classes tends to one, i.e. one class containing all the pixels of the image (see fig. 6 and 7).

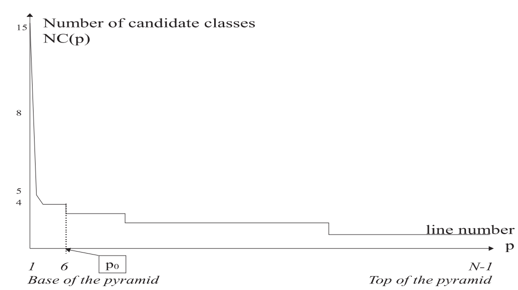


Figure 7: Variation of $NC(p)$ corresponding to fig. 6

Fig. 6 illustrates the behavior of $NC(p)$, evaluated from the analysis of a $NCDP$.

Fig. 7 represents the function $NC(p)$ of fig. 6. At the base of the pyramid, $NC(1)$ is equal to 15, $NC(2)$ is equal to 8, $NC(3)$ is equal to 5, then $NC(i)$ is equal to 4 for $i \in [4,...,6]$.

In the current version of our algorithm, we progress from the base of the pyramid to the top and we stop the analysis where the number of candidate classes is stabilized.

The analysis of the variations of $NC(p)$ of fig. 7 shows that the first range of p for which $NC(p)$ becomes stable starts at $p_0 = 6$. So $NC(p_0) = 4$ is the actual number of classes.

4.3 Analysis of each class

4.3.1 Introduction

Once the $NC(p_0)$ classes C_j are detected, each class has a core $S[k_j^{p_0}, k_j^{p_0} + p_0]$.

It's possible that a set $S[k_j^{p_0}, k_j^{p_0}+p_0]$ represents the core of different classes which are merged into C_j. In this case, the class C_j must be split into different classes.

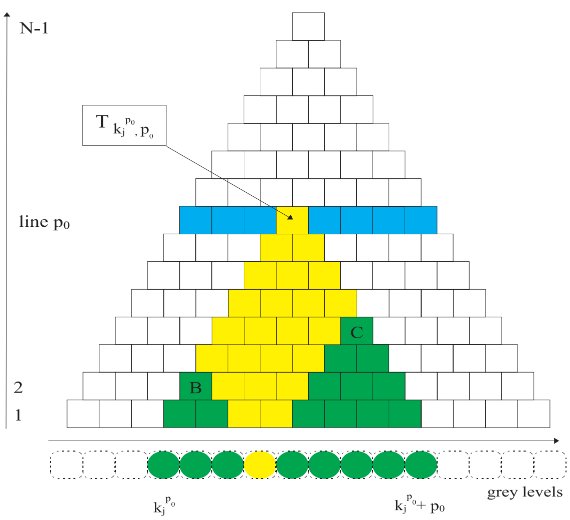


Figure 8: A class constituted of two distinct cores

Let's consider the example of fig. 8. Our method determines a local maximum represented by $T_{k_j^{p_0},p_0}$. The cell $T_{k_j^{p_0},p_0}$ corresponds to a class core $S[k_j^{p_0}, k_j^{p_0} + p_0]$ which has an high normalized connectivity degree. If this set of pixels contains two different and not connected sets B and C which constitute each a distinct class, the class which is associated to $T_{k_j^{p_0},p_0}$, must be split into two different classes.

4.3.2 Second analysis

In order to verify if a class core $S[k_j^{p_0}, k_j^{p_0}+p_0]$ isn't constituted of not connected class cores, we build a new $NCDP$ whose base is included between $k_j^{p_0}$ and $k_j^{p_0} + p_0$. This pyramid contains p_0 lines. (See fig. 9)

The analysis method of this $NCDP$ is described in paragraph 4.2. That is to say, it's based on the evaluation of the number of candidate classes with the MAX-MIN method on each line.

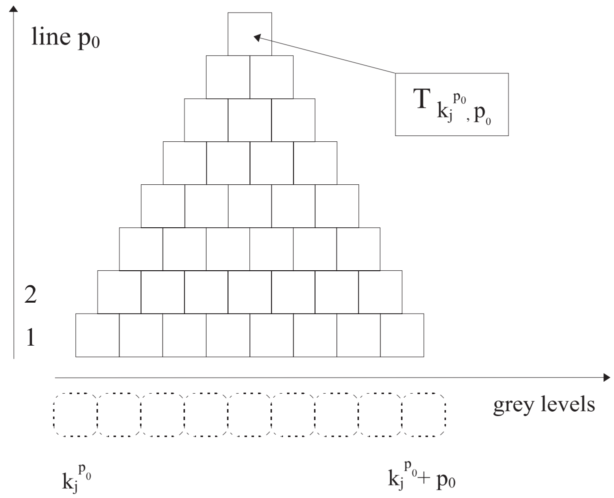


Figure 9: New pyramid with grey levels base $[k_j^{p_0}, k_j^{p_0} + p_0]$

If the analysis yields one class, that means that the core is constituted of one set of connected pixels. The class C_j musn't be divided.

On the contrary, if the number of actual classes is greater than one, the class C_j must be split into subclasses

After the analysis of each class, we determine the new number of classes Nc and their cores. We note $S[min_{C_j}, max_{C_j}]$ the final core of each class C_j with $j = 1, ..., Nc$.

4.4 Pixels classification

Our classification scheme is based on the probabilities comparison of a pixel to belong to a class. This probability is evaluated in accordance with the grey level of the pixel and the cooccurences of grey levels in the image. A pixel is labelled to a class if its probability to belong to this class is greater than the other probabilities.

Let's note $\mu_{C_j}(P(x,y))$, the probability for a pixel $P(x,y)$, whose grey level is $g(x,y)$, to belong to a class C_j.

If $P(x,y)$ belongs to the set $S[min_{C_{j_0}}, max_{C_{j_0}}]$, which represents the core of the class C_{j_0}, then: $\mu_{C_{j_0}}(P(x,y)) = 1$ and $\mu_{C_j}(P(x,y)) = 0 \quad \forall j \neq j_0$.

If $P(x,y)$ doesn't belong to any core of class, then the probability of $P(x,y)$ is evaluated as a function of cooccurences.

In this case, we propose to evaluate the probability of

$P(x,y)$ to belong to the class C_j by:

$$\mu_{C_j}(P(x,y)) = \frac{1}{max_{C_j} - min_{C_j} + 1} * \sum_{l=min_{C_j}}^{max_{C_j}} \frac{Occ(g(x,y),l)}{\sum_{m=0}^{N-1} Occ(g(x,y),m)} \tag{7}$$

where $Occ(g_1, g_2)$ is the number of occurences in the image of a pixel with grey level g_1 in the 8-neighborhood of a pixel with grey level g_2.

5 Results

In order to illustrate our method, we choose a part of a fundus image which contains 5 kinds of regions (See fig. 10), namely :

- The papilla where the veins merge,
- The eye fundus which is constituted of healthy cells,
- The veins,
- A heart of the retinitis lesion,
- The transition between the eye fundus and the heart of a lesion. These pixels represent the cells which may be contaminated by the lesion.

Our algorithm has unsupervisely identified 10 classes. We have represented the classification results by an image of labelled pixels. The grey level of a labelled pixel is the mean of the grey levels of the corresponding class. (see fig. 11).

In the area of interest, we can identify 5 main classes:

- C1 : Pixels which represent the heart of the lesion,
- C2, C3, C4 : Pixels which represent the transition zone between the lesions and the healthy cells
- The other classes : The veins and the eye fundus.

The close examination of fig. 11, shows that the lesion's hearts are well segmented. Thanks to our scheme, we detect different levels of transition between healthy and infected cells. This gives an interesting representation of a lesion to the ophthalmologists. With such a labelled image, our system can provide the basis for further geometric measures of the lesions.

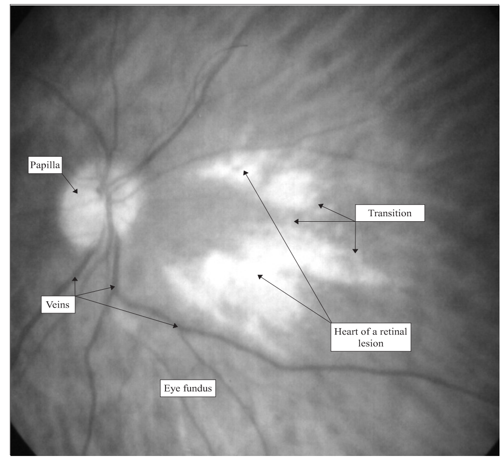


Figure 10: Image of a fundus

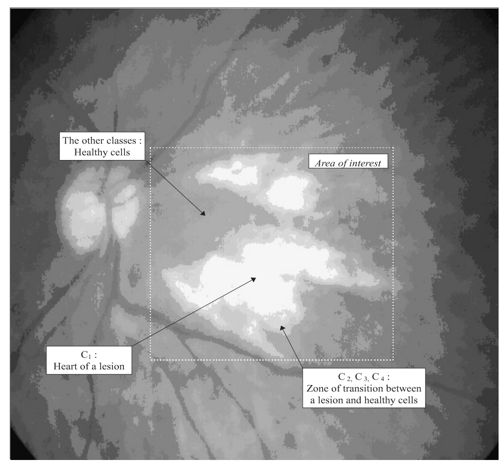


Figure 11: Image of the labelled pixels

6 Conclusion

In this paper, we have presented an original unsupervised segmentation scheme which splits a grey level image into different sets of connected pixels whose grey levels are homogeneous. This approach is based on an analysis of a triangular table denoted "Normalized connectivity degrees pyramid". This method is used in order to detect cytomegalovirus retinitis lesions by fundus image analysis. First, we determine the number of pixels classes and their cores. The core of each class C_j is represented by an interval of grey levels $[min_{C_j}, max_{C_j}]$. For classification purpose, the pixels whose the grey level belongs to such an interval are labelled to the corresponding class. The other pixels are assigned by comparison of their conditional probability to belong to the different classes. The ophthalmologists are presently evaluating the accuracy and the performance of this algorithm in field conditions with large populations of subjects. Furthermore, we are looking for the generalization of our scheme to color image segmentation.

References

[1] K.S. Cheng, J.S. Lin, and C.W. Mao. ”The application of competitive hopfield neural network to medical image segmentation”. *IEEE Transactions on Medical Imaging*, 15(4):560–567, 1996.

[2] S. Vitulano, C. Di Ruberto, and M. Nappi. ”Different methods to segment biomedical images”. *Pattern Recognition Letters*, 18:1125–1131, 1997.

[3] J.K. Udupa. ”Multiple sclerosis lesion quantification using fuzzy-connectedness principles”. *IEEE Transactions on Medical Imaging*, 16(5):598–607, 1997.

[4] M. Goldbaum, S. Moezzi, A. Taylor, S. Chatterjee, J. Boyd, E.Hunter, and R. jain. ”Automated diagnosis and image understanding with object extraction, object classification, and inferencing in retinal images”. *IEEE International Conference on Image Processing*, 3:695–698, 1996.

[5] R. Schettini. ”A segmentation algorithm for color images”. *Pattern Recognition Letters*, 14:499–506, 1993.

[6] N.R. Pal and S.K. Pal. ”A review on image segmentation techniques”. *Pattern Recognition*, 26(9):1277–1294, 1993.

[7] A. Tremeau and N. Borel. ”A region growing and merging algorithm to color segmentation”. *Pattern Recognition*, 30:1191–1203, 1997.

[8] L. Macaire and J-G. Postaire. ”Automated visual inspection of galvanized and painted metallic strips”. *7th IEEE Annual European Computer Conference COMPEURO 93*, pp. 8–15, may 1993.