Unsupervised Bayesian Classifier Applied to the Segmentation of Retina Image

C. Banga*, F. Ghorbel* and W. Pieczynski**
Groupe IMAGE, Institut National des Télécommunications -
*ENIC, 6, rue des techniques 59658 Villeneuve d'Ascq CEDEX France.
**Département Systèmes et Réseaux, 9, rue Charles Fourier Evry France.

Abstract- **In this paper, we use a stochastic model based on the finite normal mixture distribution identification for retina image segmentation. Local unsupervised methods blind and contextual, using the Expectation-Maximisation (EM) family algorithms for parameter estimation are tested. To get rid of the spatial dependence effect of pixels, a decorrelation processing is used before parameter estimation. The segmentation is then performed by Bayesian decision rule. Segmentation results are presented to prove the effectiveness of different approaches.**

I. INTRODUCTION

Segmentation of medical images is a well-known complex problem [2], particularly when images are not planar or noisy. In this framework, we compare some recent segmentation algorithms based on unsupervised Bayesian classification. The EM family methods will be compared in the contextual and blind cases. We apply those algorithms to retina image segmentation. Shape singularities in the case of retina show that some kind of algorithms are more suitable than others.

II. THE EM FAMILY ALGORITHMS

The blind approach presented below does not use neighbourhood information for image segmentation. Suppose an image be a mixture distribution realization; its probability density function (pdf) is given by :

$$h(x) = \sum_{j=1}^{k} p_j f_j(x); \quad 0 \leq p_j \leq 1; \quad \sum_{j=1}^{k} p_j = 1 \qquad (1)$$

where p_j is the a priori probability for the j th pattern class, and k is a majorant of the total number of classes in the image, $f_j(x)$ represents the conditional pdf of class j. In Bayesian unsupervised classification using parametric estimation, the problem of segmentation is based on the mixture distribution identification. In this paper, we suppose that $f_j(x)$ is a Gaussian function $f(x,a_j)$ with parameter vector $a_j=(m_j,q_j)^T$, m_j and q_j are respectivily the expected value and the variance of class j. To estimate this vector, the EM family algorithms propose four steps in solving the likelihood equation, given an available sample $x_1,x_2,\dots x_N$ from the image. The parameters m_j and q_j are initialized from histogram, while p_j are set to $1/_k$.

1) Estimation step: The a posteriori probability for a pixel $(x_i)_{i=1\dots N}$ to belong to the j th pattern class at the n th iteration is given by:

$$t_j^n = p_j f\left(x_i, a_j^n\right) / \sum_{l=1}^{k} p_l f\left(x_i, a_l^n\right) \qquad (2)$$

2) Stochastic step: We construct a Bernoulli random variable z_j^n of parameter t_j^n .

3) Annealing step: From the random variables t_j^n and z_j^n we construct an other random variable r_j^n so that,

$$r_j^n(x_i) = t_j^n(x_i) + g_n\left(z_j^n(x_i) - t_j^n(x_i)\right) \qquad (3)$$

where (g_n) is a sequence which slowly decreases to 0.

4) Maximisation step: $r_j^n(x_i)$ is considered artificially as the a posteriori probability of x_i, so that at the (n+1) th iteration, we have:

$$p_j^{n+1} = \left(N \sum_{i=1}^{N} r_j^n(x_i)\right)^{-1}; \; m_j^{n+1} = \sum_{i=1}^{N} x_i r_j^n(x_i) / \sum_{i=1}^{N} r_j^n(x_i)$$

$$q_j^{n+1} = \sum_{i=1}^{N} r_j^n(x_i)\left(x_i - m_j^{n+1}\right)\left(x_i - m_j^{n+1}\right)^T / \sum_{i=1}^{N} r_j^n(x_i) \qquad (4)$$

The algorithm stops when the condition $|p_j^{n+1} - p_j^n| < d$ is satisfied, with d a given small number.

EM algorithm assumes $g_n=0$, so that the stochastic and annealing steps are not necessary. EM leads in many cases to an acceptable estimator of parameters. However, the result obtained is sometimes dependent on the algorithm initialiazation, so that the EM algorithm could converge to a bad solution. SEM algorithm assumes $g_n=1$. The Annealing step is not necessary. SEM introduces a stochastic step in EM algorithm, so that it would converge rapidily to the good solution. SAEM algorithm assume all the four steps necessary. It is an intermediate algorithm that reduces the randomization intensity of SEM (g_n decreases to 0) and converges to EM algorithm during iterations [3]. The contextual approach uses information coming from the neighbour pixels interaction for mixture identification. In this case, we suppose X is the random field whose the real image is a realization. X field is divided in a finite number

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of local fields X_v, where v is a given neighbourhood of a given pixel s. The discriminant functions in (1) become

$$\sum_{j=1}^{k^{z-1}} p_{lj} f_{lj}$$

z is the number of elements in v; f_{lj} is the conditional pdf of X_v given: j is the class of pixel s and, l represents the classes of the neighbour pixels of s. So that for the gaussian parametric estimation, $f_{ij}(x)=f_i(x,a_j)$, where $a_j=(m_j,q_j)^T$ m_j becomes the expected vector and q_j the covariance matrix

III. Results and discussions

We apply the EM family algorithms to retina images which are photographs of 512 x 512 pixels. For the blind approach algorithms, we randomly selected a 1000 pixel size reprentative sample for parameter estimation. Fig. 1 represents the original retina image. Fig. 2 and 3 give respectivily the segmented image obtained by SEM and SAEM algorithms. The contextual SEM algorithm was performed in the case of one neighbour pixel, the result obtained is shown by fig. 4. Some conclusions can be deduced : the contextual approach gives good results for homogenous regions. However, it appears not suitable for extracting contour information (blood vessels). To decrease the great dependence of neighbour pixels, it is more suitable to choose a random representative sample from the original image for maximum likelihood parameter estimation. With this kind of sample selection, we show that EM family algorithms in the blind case give better results than the contextual ones, for the retina image segmentation with less computing time. The main reason for choosing segmentation is data compression and invariant description of retina images in our future investigations.

Figure 1 : the original retina image

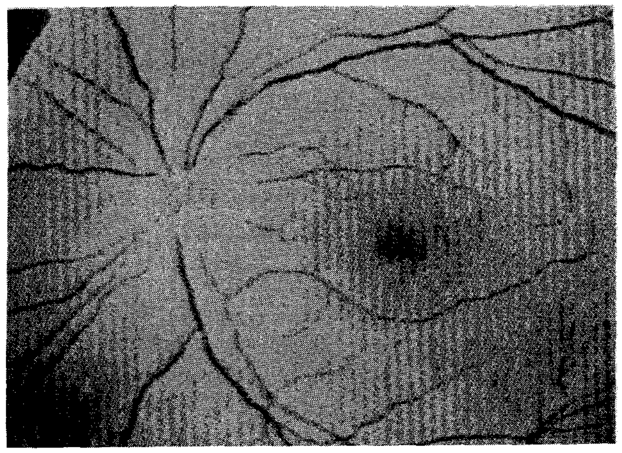

Figure 2 : Segmented image by blind SEM algorithm.

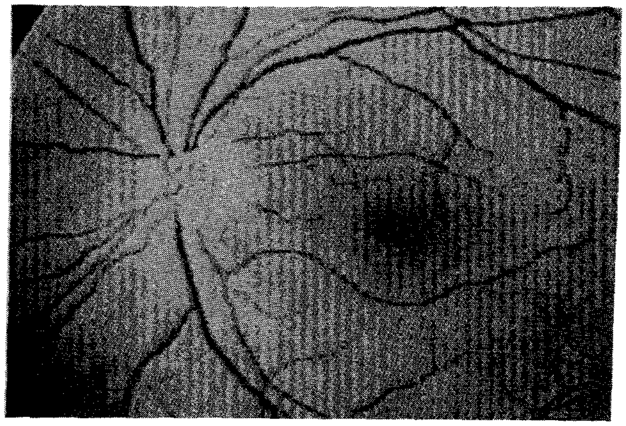

Figure 3 : Segmented image by blind SAEM algorithm.

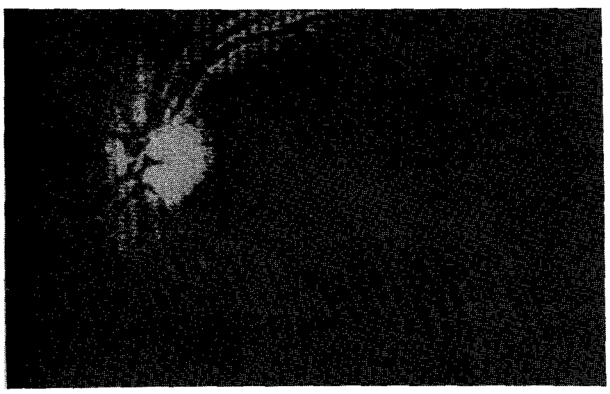

Figure 4 : Segmented image by contextual SEM algorithm.

References

[1] Pieczynski W., *Estimation of context in random field,* Journal of Applied Statistics, vol. 6, n°2, 1989.

[2] T.Lei and al, *Statistical Approach to X-Ray CT Imaging and its application in image Analysis Part II: A new stochastic model-based...*, IEEE Trans. on Medical imaging, vol. 11, n°1, pp 62-69, March 1992.

[3] C. Soubiran and al, *Analyse de mélanges gaussiens pour de petits échantillons: Application à la cinématique stellaire*,Revue de Statistique Appliquée, vol. 39, n° 3, pp 17-35, 1991.