ADAPTATIVE SEGMENTATION OF SAR IMAGES

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***Abstract* - Our work deals with the unsupervised segmentation of radar images. Usually the marginal distribution of each class for SAR image segmentation is supposed Gaussian or Gamma, the field of classes is generally supposed stationary. We propose the use of different marginal distributions in order to improve the fitness of the statistic model with the data. The distributions grouped in the Pearson system provide an approximation to a wide variety of observed distributions like in radar image of the sea, ice, ... To take into account the non stationarity of the class field we adopt of a new modelization for this field. The mixture of marginal distributions and therefore the class field distribution are estimated by an adaptative algorithm. We adopt Bayesian criterion for image segmentation. The algorithm obtained is tested on a synthetic image and also applied to the segmentation of real SEASAT scene.**

***Résumé* - Le but de notre étude est la segmentation statistique des images radar. Les méthodes de segmentation classiques supposent généralement l'existence d'une seule famille de lois commune à toutes les classes de l'images. On suppose généralement aussi la stationarité du champ de classes. Dans cet article nous proposons l'utilisation du système de distribution de Pearson pour la modélisation du champ de mesures. Nous tenons compte ainsi de la variété de lois et des paramètres dans l'ensemble des classes de l'image. Nous proposons aussi un modèle non stationnaire pour le champ de classes. La distribution des deux champs: classes et mesures sont estimées par une méthode itérative adaptative. Le critère de classification bayesien est adopté lors de l'étape de segmentation. L'algorithme de segmentation obtenue est testé sur des images de synthèses et des images SEASAT réelles.**

I. INTRODUCTION

Image segmentation is one of important problems in computer vision. It aims to identify each pixel by its class. In the SAR images case, these classes are the homogeneous regions of the image. Their histogram shape allows a statistical modelisation which is described by the HIM model. An image is therefore modelised by the unknown field of classes X and an observed field of measurements Y. The problem of segmentation is then the problem of estimation of the unknowing field of classes knowing the field of measurement. In order to estimate the field of classes authors suppose generally only one law for each conditional probability density function for Y given X. They also suppose stationarity of the field X. Segmentation algorithms developed from this model yield sometimes insufficient results[4]. In this paper we propose a modelisation of the field of classes which takes into account the non-stationarity of this field. The field of measurement is modelised by a mixture of laws belonging Pearson system [1,3,7]. Due to this modelisation the segmentation algorithm developed is closer to the reality.

II. MODELS FOR RADAR IMAGES

When considering statistical segmentation of images authors generally suppose the existence of two random fields : the field of "classes" $X = \{X_s : s \in S\}$ and the field of measurement $Y = \{Y_s : s \in S\}$.

Each X_s takes its value in a finite set $\Omega = \{\omega_1, ..., \omega_K\}$ of classes and Y_s in IR. So the problem of segmentation is the problem of the estimation of an ignored realisation of X from an observed realisation of Y. We will suppose that the realisation of Y depends on the realisation of X and a certain "noise". The distribution of (X, Y) is defined by P_X the distribution of X and the family $P_Y^{X=x}$ of distribution of Y conditional to X = x.

The hierarchical model [6] adopts this proceeding, it consists on two random fields. One governs the grouping of the pixels called region process and the other consists of K random fields which represent the noise degraded appearance of the nature, the classes. These K random fields modelize class inherent statistical properties and system inherent noise. We have chosen Kelly and Derin's image model for two reasons.

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Firstly, this model clearly points out that the texture "observed speakle" is not only a worthless disturbance, but carries information on the nature of the ground. Secondly, the hierarchical character fits well to Bayesian decision theory and this model allows quite easily the generation of a great number of synthesised images with real radar image statistics.

Region process : The region process is responsible of the distribution pixels within the different classes. An image consists of a few different region types. There is some spatial continuity in the way that a pixel is likely to be from the same region as nearby pixels. This process is described by the field of classes X. In our case we suppose the random variable X_s dependant on each pixel location. Its law is given on each pixel by the priori probability $\Pi(X_s)$, we then suppose the independence of the random variables X_s

Speckle process :This field cannot be observed, so the speckle process modelizes the marginal statistics of each type of observed nature. Kelly and Derin derived the intensity distribution of a single pixel in the case of a narrow band pulse of a typical coherent imaging system, which was found to be also the marginal distribution. Unfortunately empirical and theorical studies have shown that nature does not always follow these distributions. So not all scenes can be represented by the same distribution.

We propose a system of distributions, the Pearson system, which englobes nearly all well-known unimodal densities. Our speckle process consists therefore of K random fields, where every field is a realisation of one distribution in the family of distributions proposed by Pearson. In the following chapter, the Pearson system will be explained.

III. USE OF THE PEARSON FOR THE DIFFERENT MARGINAL DISTRIBUTIONS

We suppose that the fields are characterised by homogeneous textures. Each type of texture corresponds to a distribution of the grey level. Here the fields are supposed to be characterised by a parametric law belonging the system of Pearson distributions [7].

The system of distributions has been made up so that it provides approximations to as wide variety of observed as is possible. The shape of distributions Pearson varies significantly since the probability density function can be either bell shaped, U shaped or J shaped. This flexibility of the parametric distributions allows to obtain a good approximation of the histogram of the field.

The Pearson system's distributions satatisfay:

$$\frac{df_U^{\omega_k}(u)}{du} = -\frac{u+a}{c_0+c_1u+c_2u^2} f_U^{\omega_k}(u)$$

a, c_0, c_1, c_2 are the parameters of the distribution.

Where U is the grey level of the image and the $f_U^{\omega_k}$, $k \in \{1, 2, ..., K\}$ the conditional probability densities to the class ω_k.

The shape of the distribution depends on the parameter a, c_0, c_1 and c_2. Pearson classifies the shape into eight different types. We can show in fig. 1 that β_1 and β_2 are sufficient to differentiate these ones.

$$\beta_1 = \frac{\mu_3^2}{\mu_2^3} = \text{skewness} \quad \beta_2 = \frac{\mu_4}{\mu_2^2} = \text{kurtosis.}$$

with $\mu_\alpha = E\left[(U - E[U])^\alpha\right]$

These parameters characterise the dissymetry and the flatness of the distribution. They are invariant by translation of the grey level. The invariance property is significant for the radar images because calibration is performed for each scene and the gray level is not representative of the level for the scattering of the observed area. For each scene, we calculate β_1 and β_2 and represent it in the graph(see fig. 1) by a point.

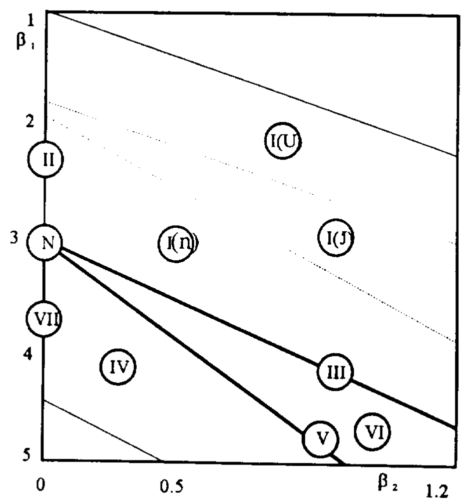

fig. 1 : Pearson graph

IV. ADAPTATIVE ESTIMATION OF PARAMETERS

We will expose in this chapter the new adaptative algorithm we propose. It aims to estimate all parameters defining the components of the distribution mixture as the shape of the marginal distributions of classes.

Parameters θ_k $k \in \{1, 2, ..., K\}$ defining the conditional distribution of Y given the field X are estimated in a first step by the SEM algorithm [8].

Algorithm run :

a. SEM algorithm for all the image

The priori probabilities $\Pi_{k,s}$ $k \in \{1, 2, ..., K\}$ defining the distributions of the field of classes are temporary chosen as independent of the location s : $\Pi_{k,s} = \Pi_k$. To estimate θ_k and Π_k, we use the SEM algorithm as follow :

Initialisation : t=0

$\Pi_k^{t=0}$ and parameters defining $f_k^{t=0}$ are chosen as random.

Step S : t > 0

For each y_s we draw a realisation $e^t(y_s)$ from the set E with regards to the conditional distribution knowing $X_s = x_s$. We obtain a new partition $(Q_1,...,Q_K)^t$ of the image in K classes and $\beta_{1,k}$, $\beta_{2,k}$ with the help of the couple $(\Pi_k, f_k)^t$.

Step E:

For defining the best sitting density f_k^{t+1} of the Pearson system we estimate its parameters by the method of moments. In the last selection , we estimate Π_k^{t+1} by:

$$\Pi_k^{t+1} = \frac{card(Q_k)}{card(S)}$$

Step M :

We compute the distribution $P_{X_s}^{Y_s=y_s}$ and return to step S.

b. EM algorithm for each pixel

In this part, we take into account the non-stationarity of the class field. On each pixel s, we estimate the priori probabilities $\Pi_{k,s}$ by using the EM algorithm. The probability densities f_k are estimated in the last part.

On each pixel s, we choice the neighbourhood V_s of the pixel s, the restriction to V_s of the field X is supposed stationary.

Initialisation : t=0

$\Pi_{k,s}^{t=0}$ are chosen equal : $\Pi_{k,s}^{t=0} = \frac{1}{K}$, k= 1, 2 , ..., K.

Posteriori probabilities $P_{X_s}^{Y_s=y_s}(x_s)^{t=0}$ are estimated by Bayesian rule.

Step E : t>0

We estimate the new priori probabilities by:

$$\Pi_{k,s}^{t+1} = \frac{\sum_{V_s} P_{X_s}^{Y_s=y_s}(X_s = \omega_k)}{card(V_s)}$$

Step M :

We compute the distribution $P_{X_s}^{Y_s=y_s}$ and return to step E.

V. BAYESIAN APPROACH

The density of Y_s conditional to $X_s = x_s$ and the distribution of the classes X_s define the distribution of (X_s, Y_s) and therefore the conditional distribution of X_s knowing $Y_s = y_s$.

The Bayesian rule r_g is then defined by :

$$r_g(y_s) : \hat{x}_s \Leftrightarrow P_{X_s}^{y_s}(\hat{x}_s) = \sup_{x_s} P_{X_s}^{y_s}(x_s)$$

It can be also written as follow :

$$r_g(y_s) : \hat{x}_s \Leftrightarrow \Pi_{\hat{x}_s} f_{Y_s}^{\hat{x}_s}(y_s) = \sup_{x_s} \Pi_{x_s} f_{Y_s}^{x_s}(y_s)$$

The r_g function is called "discriminating".

VI. EXPERIMENTAL RESULTS

We present some estimation and segmentation results.

In order to show the efficiency of our adaptative algorithm, we compare results obtained by our algorithm to those obtained by classic method, wich suppose stationnary the field of classes. Two sorts of images are segmented:

-The synthetic images which allow the valuation of our estimator performance and also the comparison of the rate error obtained by the adaptative segmentation method to the classic one.

-The SAR images allowing to show that we have not necessarily the same law for the grey level of each class.

a. Simulated image

We consider a two classes image representing rings. The two classes of the noisy image are characterised by the same means μ, closed variance σ^2 and different shape parameters β_1, β_2. The mixture estimation results are summarised in table 1. they point out the ability of the SEM algorithm to estimate the distributions mixture since the estimated parameters are close to their true value. Fig 1 contains the

original noised image. The noised image segmented by the classic method is shown in fig 2. the rate error of classification by this method is about : 0.4.
The fig 3 contains the same noised image, segmented by the adaptative method. The rate error of classification is about :0.1 . This results shows therefore clearly the superiority of our adaptative classification method in non-stationary scene.

	parameters	Th	exp
Class 1	μ	140	140
	σ^2	150	152
	β_1	0.5	0.5
	β_2	3.7	3.4
	law	1	1
Class 2	μ	140	140
	σ^2	150	149
	β_1	1.5	1.5
	β_2	5.5	5.5
	law	6	6

Table .1

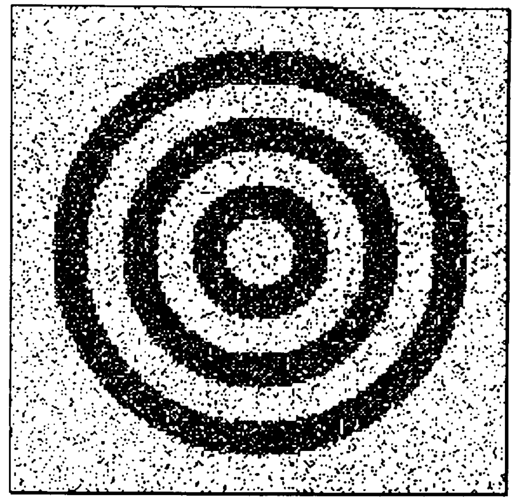

Fig. 2

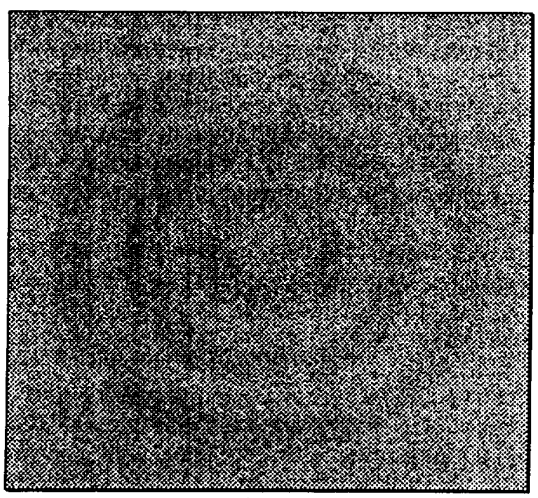

Fig. 1

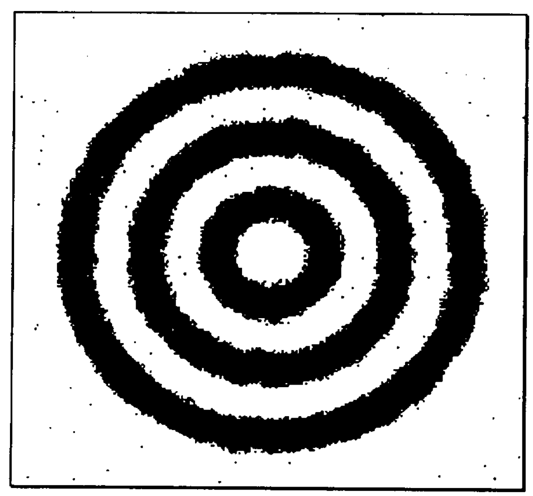

Fig. 3

b. SAR image case

We present in this part the segmentation of a four looks image of the Brittany coast (Fig. 4). This image has been segmented by the two methods : the adaptative presented method (Fig. 6) and classic one (Fig. 5). Estimation results are shown in table 2. Lut us remark that laws of the grey level distribution of the two classes are not the same. As expected the adaptative segmentation method derives more satisfying results. There's a better discrimination of the homogenous regions.

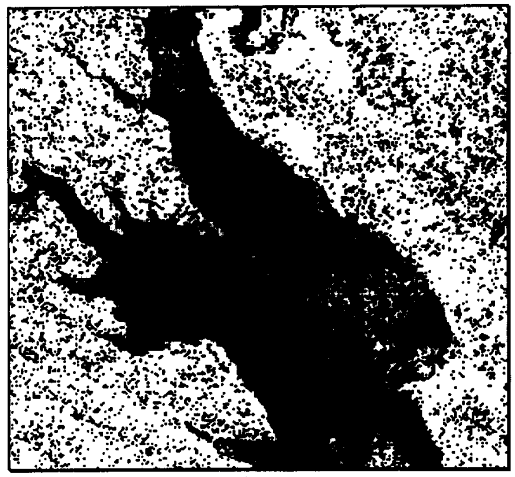

Fig. 5

	parameters	*exp*
Class 1	μ	22
	σ^2	52
	β_1	0.1
	β_2	2.9
	law	1
Class 2	μ	57
	σ^2	500
	β_1	3.6
	β_2	10
	law	6

Table. 2

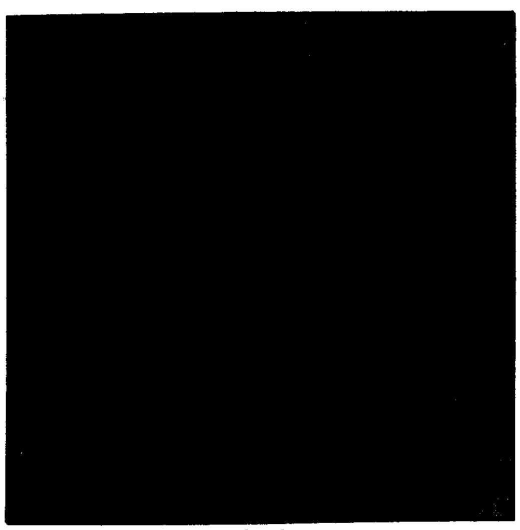

Fig. 4

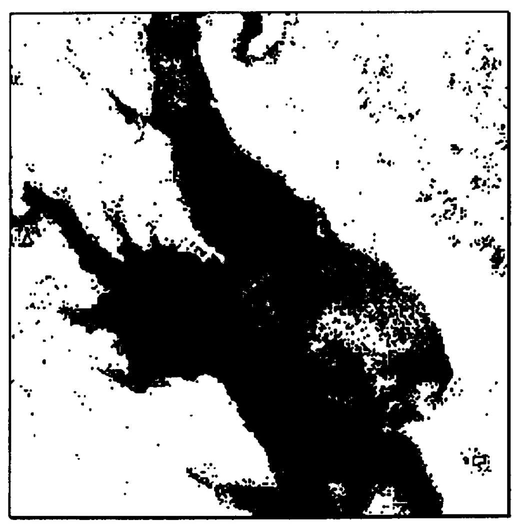

Fig. 6

CONCLUSION

We exposed a new local segmentation method and showed that it can take into account the non-stationarity of the class field.

We used Pearson system to modelize noise of each class, the results obtained showed therefore different distribution laws of the each class grey level. We explained the adaptative segmentation method permitting to take into account the non-stationarity of the class field.

Results obtained by this method seem to be satisfying. Our modelisation of the random class field does not taken into account the dependence of its components. Markovien methods[9,10] can therefore used in this case.

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