Comparative Study Of Some Algorithms for Terrain Classification Using SAR Images.

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ABSTRACT

This paper describes the use of polarimetric SAR data for earth terrain identification and classification. The K-distribution previously described in the literature is used to describe the spatial characteristics of forest area. Statistical methods using supervised and unsupervised techniques are also applied to segment the simple and the polarimetric data. The supervised classification is based on the ML algorithm assuming a Rayleigh distribution for the intensity pixels of the HH image and a circular Gaussian for the full polarimetric data. For the unsupervised classification, we use both the clustering and the ICM (Iterative Conditional Modes) algorithms.

Using such techniques, the segmentation is no perfect as we would classify areas of trees which differ by their age and which have in general an approachable scattering behaviour.

1. INTRODUCTION

Extracting reliable information from radar returns is one of many important steps toward the accurate classification of terrain cover. With the use of the polarimetric multifrequency data, the discrimination of terrain cover can be significantly improved. Several techniques have been developed recently to analyse polarimetric radar data for earth science applications. From the received waves, a number of polarimetric radar analysis techniques have been recently reported in the literature to measure and characterize the polarization response of natural terrain cover in order to classify SAR data such as polarimetric signature, fractional polarization, coefficient of variation...SAR data have also received some attention in terms of segmenting them into edges or regions. In this paper, the texture information is extracted from polarimetric data to characterize each class of the scene imaged. The statistical properties of high resolution polarimetric SAR data are examined using the K-distribution [1] which is the result of the presence of both speckle and texture information in SAR images. This distribution, by means of one parameter α, can characterize each class of the cover. The ability to use the texture information as a classification tool is very dependent on sensor parameters such as the frequency. Next, two algorithms of terrain cover classification are used: supervised and unsupervised techniques. They yield a more quantitative facility to interpret the SAR images. For the supervised classification, the maximum likelihood (ML) polarimetric classifier is applied by assuming a Rayleigh distribution for simple polarimetic data and a circular Gaussian for the fully polarimetric complex data [2]. Confusion may occur between regions and the resulting segmentation maps are not satisfactory and appear noisy. Unsupervised classification is based first on the multidimensional clustering algorithm [3] and then on the ICM (Iterative Conditional Modes) algorithm [4] which is an approximation of the simulated annealing. This algorithm is implemented using the MAP (Maximum a posteriori) distribution. Given the polarimetric measurement vector, the posterior distribution of the region labels is maximized.

The paper is structured as follows. The third section reports on the exploit of the cover texture by the mean of the amplitude information to distinguish between different scattering behaviour. The parameter α is used as a discriminator of the different class of trees and clear cut regions. In section 4, supervised and unsupervised classification procedures are applied to synthetic aperture radar polarimetric images in order to identify their various components then the performance of these techniques are evaluated using single and a full polarimetric data.

2. EXPERIMENTAL DATA

The results are obtained from data measurements of the MAESTRO-1 campaign made by the NASA/JPL polarimetric AIRSAR system which operates at P (0.44 GHZ), L (1.225 GHZ) and C (5.3 GHZ) frequency band with an incident angle ranging approximately from 40^{o} to 50^{o}. The campaign measurements were made on the 16 of august 1989 when meteorological and environmental conditions are optimal in France. All data are in the form of one-look resolution complex scattering matrix and each pixel represents 6.66 m in slant range and 3 m in azimuth on the ground. The test-site selected is a Forest (Les Landes) in southwestern France (near Bordeaux). It is almost totally formed of maritime pine (pinus pinaster) and consists of a section of forest where trees are of different ages and clear cut regions.

For the experimental results, we have selected five regions of trees which differ by their ages (from one to 46 year old) and clear cut region.

Figure 1 represents the HH image of the test-site at P-band with a look direction parallel to the row direction.

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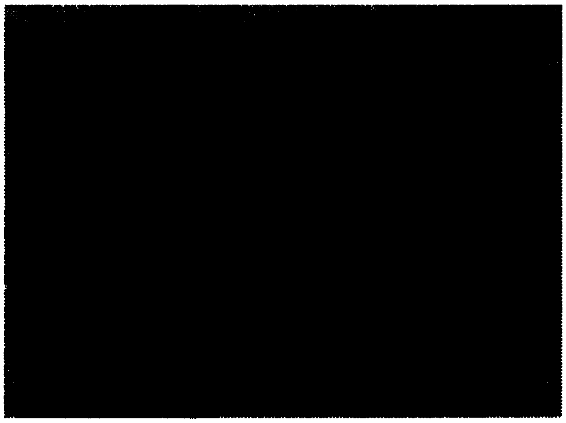

Fig.1. HH image in P- band

3- AMPLITUDE CHARACTERIZATION OF THE POLARIMETRIC DATA

Among the many functions available, the K-distribution provides good agreement when used to characterize the amplitude of electromagnetic echoes from cover such as forest areas. This distribution is derived with one parameter α. The variation of this parameter, which is closely related to terrain heterogeneity, characterizes each class of the cover with respect to its degree of spatial heterogeneity. The probability density function PDF of the received amplitude is given by:

$$p(A) = \frac{2b}{\Gamma(\alpha)}\left[\frac{bA}{2}\right]^{\alpha} K_{\alpha-1}(bA) \qquad \alpha > 0$$

where $b = 2\sqrt{\alpha / \langle A^2 \rangle}$ and A can be the amplitude of HH, HV or VV.

The parameter α, for each polarimetric channel, can be found by equating the theoretical second-order normalized intensity moment given by $I^{(2)} = 2(1 + 1/\alpha)$ and the experimental second-order normalized intensity moments [5]. If the number of pixels chosen for each region is sufficient to ensure the meaning of the distribution statistics, then the experimental second-order normalized intensity moments of HH, HV and VV are approximately equal. To estimate the parameter α for each region and at each frequency band, we take the average of the three values. Higher order normalized intensity moments versus second order intensity moments for several patches of trees which differ by their age at P, L and C frequency band are potted in figure 2, 3 and 4 respectively.

The experimental normalized intensity moments agree very well with the theoretical higher-order normalized intensity moments of the K-distribution represented by the solid curves. Hence each class of trees can be characterized by one parameter α.

Young trees (1-5 year old), because of their small height appears more heterogeneous then mature trees. The soil surface contributes significantly. Therefore, these regions are characterized by small values of α (2 at P band). In mature trees, the contribution of the soil surface becomes less important and volume scattering is more dominant. Hence, they will appear less heterogeneous and the parameter α increases (5.3 at P band for 44-46 year old trees).

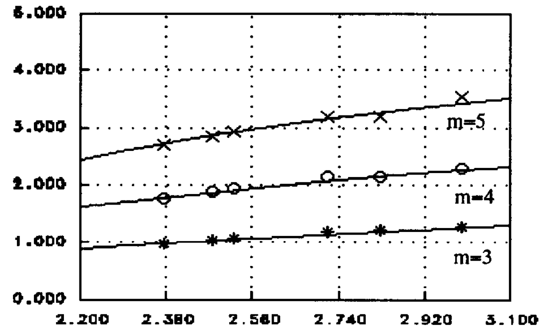

Fig 2 Higher-order normalized intensity moments versus second-order normalized intensity moment in P-band - Theoretical K-distribution

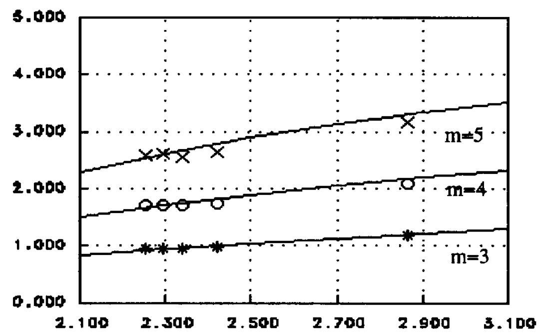

Fig.3.Higher-order normalized intensity moments versus second-order normalized intensity moment in L-band - Theoretical K-distribution

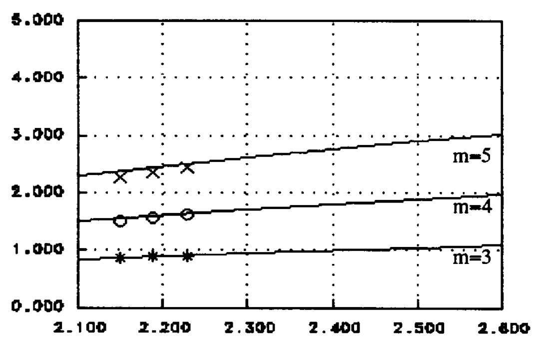

Fig.4.Higher-order normalized intensity moments versus second-order normalized intensity moment in C-band - Theoretical K-distribution

In figure 5, we compare the theoretical PDF of the K distribution represented by the solid curve with the histogram of normalized HH amplitude for 1-5 year old trees. The result shows the good agreement of the K-distribution with the experimental data.

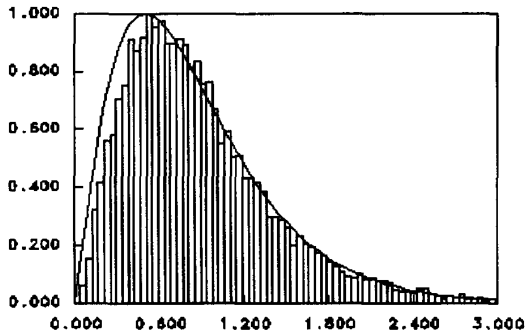

Fig.5.Histogram of normalized amplitude HH of trees 1-5 years in P-band - theoretical K-distribution

Another common concern is the effect of the frequency on the backscattering coefficient and therefore on terrain heterogeneity. In fact, waves at C-band remain within the appear regions, while at P-band, the waves may penetrate at the lower crown regions and reach the soil. Therefore, the scene is regarded as more heterogeneous than at C-band. For example the parameter α is estimated to be 2 at P-band, 2.32 at L-band and 8.74 at C-band for 1-5 year old trees. Hence as a function of the frequency, each class of trees have an appropriate scattering behaviour and can be characterized by one parameter α of the K-distribution. heterogeneous areas (young trees) are characterized by small values of α and when the age of the trees increases, α increases (heterogeneity degree decreases).

4- SUPERVISED AND UNSUPERVISED SEGMENTATION OF SAR IMAGES

The statistical segmentation is based on the probability density functions PDF, p(y/l) the distribution for modelling texture in each region and p(l/y) the a posteriori distribution. The maximum likelihood method is based on the p(y/l) function, and the MAP (Maximum A Posteriori) method is based on the p(l/y) function. We use the Bayes law to compute p(l/y)=p(y/l).p(l)/p(y), where p(l) is deduced from the Markov model for modelling regions distribution in the image.

4.1. Image Modelling

4.1.1. Model used for the HH image

p(y/l) is the Rayleigh distribution for modelling texture inside the region. It is given by:

$$P(y/l) = \frac{2y}{\sigma_l}\exp\left(-y^2/\sigma_l\right)$$

where y is the pixel intensity and σ_l is the mean of the HH intensities, which depends on the region l.

4.1.2. Markov Model

We use the Multi_Level Logistic model (MLL), which is a particular model of Markov distribution; the PDF is given by:

$$P(l_s/l_t, t \in v_s) = \exp(-Us) / \sum_{t \in A} \exp(-Ut)$$

where l_s is the label associated to the pixel s, V_s is a neighbourhood system, U_s is the energy associated to pixel s which depends on the label l_s and A is the set of labels.

4.1.3. Model used for the full polarimetric image

The vector of three single look polarimetric complex amplitudes measured at site s by polarimetric radar is represented by $y = [HH, HV, VV]$, the conditional distribution of the single look polarimetric measurement vector **y** given its region label l is a circular gaussian

$$P(y/l) = \frac{1}{\pi^3 |C_l|}\exp(-y^+ C_l^{-1} y^T)$$

The superscript + denotes the complex conjugate and the T means the transpose of the vector. After some simplifications of the covariance matrix C_l, the expression becomes:

$$P(y/l) = \frac{1}{\pi^3}\exp\left\{-\frac{|HH|^2}{\sigma_l(1-|\rho_l|^2)} - \frac{|HV|^2}{\sigma_l\varepsilon_l} - \frac{|VV|^2}{\sigma_l\gamma_l(1-|\rho_l|^2)} + 2\Re e\frac{(HH \cdot VV^* \cdot \rho_l)}{\sigma_l\sqrt{\gamma_l}(1-|\rho_l|^2)} - \log\left(\sigma_l^2\varepsilon_l\gamma_l(1-|\rho_l|^2)\right)\right\}$$

σ_l, ε_l, γ_l and ρ_l are the polarimetric covariance parameters of each region given by:

$$\varepsilon_l = \frac{E[|HV|^2]_l}{E[|HH|^2]_l} \qquad \gamma_l = \frac{E[|VV|^2]_l}{E[|HH|^2]_l}$$

$$\rho_l = \frac{E[HHVV^*]_l}{(E[|HH|^2]_l E[|VV|^2]_l)^{1/2}} \qquad \sigma_l = E[|HH|^2]_l$$

4.2. Supervised Segmentation

In the case of supervised segmentation, the natural regions of the image are known in advance.For example, by coregistering the data with a ground map of the terrain cover, training areas may be selected to estimate the parameters of each region. The segmentation results are also quite sensitive to the selected set of training areas and a series of trials and errors is often required to obtain satisfactory results.

Using to the ML(Maximum Likelihood) ratio test, the pixel y will be assigned to the class l_i if the probability of it being in that class is greater than that of it being in any other class. Mathematically, this can be written in the following form:

l_i i=1,2,....,M classes

$y \in l_i$ if $p(y/l_i) > p(y/l_j)$ $\quad \forall i \neq j$

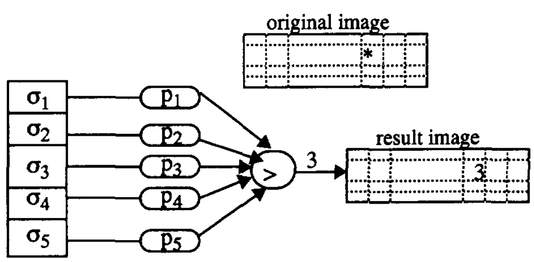

Fig.6. The ML procedure.

Using only the HH data, the results show that this algorithm is unable to classify the six regions selected as we found only two regions instead of six. The same algorithm is then applied to the full polarimetric data, and the results are improved as shown in table 1 row A:

4.3. Unsupervised Segmentation

For this purpose, we use two methods, the first is the clustering technique, the second is the ICM (Iterative Conditional Modes).

4.3.1 Clustering Technique

When training areas are not available, clustering techniques may help select the regions. A method is based on the multidimensional clustering of the vector F = (m, σ), The image is divided into a number of nonoverlapping subimages; for each of these subimages, we estimate the mean m and the standard deviation σ of the subimage. This method is based on the measure of the following normalized Euclidian distance:

$$d(F^i, F^j) = \sum_k \frac{(f_k^i - f_k^j)^2}{(f_k^i)^2 + (f_k^j)^2}$$

The results are summarized in table 1 row B.

These results are not satisfactory enough. In order to improve them, we use the ML (Maximum Likelihood) method using the MLL Markov Model. This method eliminates the misclassified pixels, refines edges and produces a 8% increase in classification accuracy as shown in table 1 row C

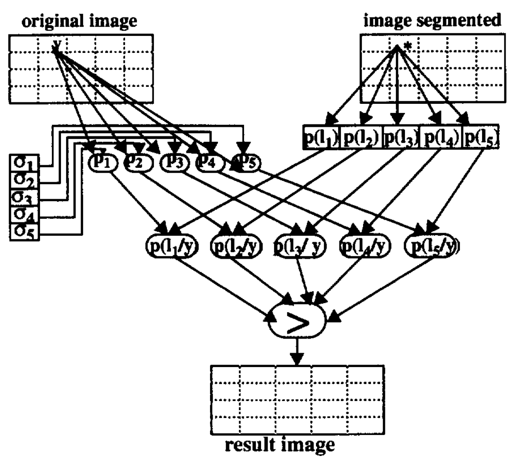

Fig. 7. ICM algorithm

4.3.2. ICM (Iterative Conditional Modes) technique

The ICM is the approximation of the simulated annealing to obtain the MAP solution, it is an iterative method which operate on pixels in image, therefore, we use the PDF: $p(l/y) = p(y/l) \cdot p(l)/p(y)$,where p(y/l) is gaussian for the three polarimetric components and Rayleigh for HH.

$p(l) = p\{l_s/l_t, t \in v_s\}$ is the MLL Markov model.

In order to obtain the approximate solution, we operate as follows:

1) The p(y/l) parameters are estimated for each region from the image segmented by clustering technique.

2) According to the Bayes maximum likelihood ratio test, the intensity y will be assigned to the class l_i if the probability of it being in that class is greater than that of it being in any other class. Mathematically, this can be written in the following form:

l_i i=1,2,...,M classes, $y \in l_i$ if $p(l_i/y) > p(l_j/y) \quad \forall i \neq j$

After a few iterations, we have an approximated solution.

The figure 7 summarizes the ICM procedure.

where $p_1 = p(y/l_1), \ldots, p_m = p(y/l_m)$.

Table 1 row D summarizes the results of ICM method applied to HH image.

The results of ICM method applied to the full polarimetric image are summarized in table 1 row E.

	area 1: 41-46 years	area 2: 33-44 years	zone3: clear cut	area 4: 6-10 years	area 5: 33-44 years	area 6: 1-5 years
A	50 %	49 %	25 %	32 %	60%	95%
B	55 %	64 %	70 %	75 %	54%	96 %
C	78%	56%	72 %	63%	63%	94%
D	89 %	50 %	85 %	55 %	71 %	95 %
E	88 %	67%	72 %	85 %	70 %	98 %

Table 1. Results of several algorithms .

5. CONCLUSION

In this paper we have shown that the K-distribution can characterize perfectly the return amplitude. By means of the parameter α which is related to the scene proprieties, we can identify each class of the terrain cover.

Using the full polarimetric data, the results of segmentation are significantly improved.

The ICM method produces good results especially when the regions have very different ages (different scattering behaviour). When the selected areas are of same age, segmentation is inefective. This result can be ameliorated by using the K-distribution instead of the Gaussian for modelling the data.

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