LAND COVER IDENTIFICATION USING POLARIMETRIC SAR IMAGES

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ABSTRACT:

Synthetic Aperture Radar (SAR) has been proven to be a powerful earth observation tool. Due to its sensitivity to vegetation, its orientations and various land-covers, SAR polarimetry has the potential to become a principle mean for crop and land-cover classification. A variety of polarimetric classification algorithms have been proposed in the literature for segmentation and/or classification of polarimetric SAR images into classes reflecting canonical scattering processes and/or some statistical properties. However, classification based on polarimetric data alone does not provide sufficient sensitivity for the separation of some classes such as forests. The use of other kinds of characteristics like texture provides better sensitivity for class separation. In this paper, we wish to address this issue, testing and comparing some polarimetric SAR classification algorithms using texture. Such an analysis will allow us to evaluate the importance of texture considering and to prove if the chosen texture model parameters describe, also, physical properties of the targets. Thus, the proposed approach is compared with the Wishart classifier showing interesting results. The test area used is the Oberpfaffenhofen in Munich and the SAR images are acquired in the P band.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) has been proven to be a powerful earth observation tool. In many remote sensing applications important additional information can be derived from multipolarised imagery. The number of studies and applications involving polarimetric SAR data is increasing steadily. Radar polarimetry has for long been known as a powerful method for soil moisture and surface roughness identification, sea ice detection and delineation of vegetation and land cover (Ferro-Famil, 2003; Macri, 2003; Hoekman, 2003; Lee, 2004; Martini, 2004; Wakabayashi, 2004; Alberga, 2007; Liang, 2008). Many features such as intensities, coherency matrix, correlation and phase differences have been used in various classification experiments.

The first algorithms developed for classification of polarimetric SAR images have ignored the spatial information (texture) and used the Whishart distribution as the basis of the classification scheme. But, th last decade, several research papers revealed the contribution of texture in polarimetric classification improvement. Thus, some authors used texture for classification without a decomposition method. Yu and Acton (2000) presented a partitioning scheme using an initial texture segmentation based on watershed algorithm. Ersahin et al. (2004) have proposed a neural network unsupervised classification scheme using covariance matrix parameters and texture features derived from gray level co-occurrence matrices. Recently, some authors proposed to employ texture features calculated from polarimetric data after decomposition. So, Beaulieu and Touzi (Beaulieu, 2004) introduced a segmentation algorithm that takes into account texture information where the K-Wishart distribution is used to model textured areas. Rodionova (2007) demonstrated that textural features defined in every scattering categories of Freeman and Durden decomposition make better object discrimination of SAR polarimetric images. In (Khan, 2007), good classification results

have been achieved using neural network with a feature set including undecimated wavelet, transform-based features and texture features along with nonlinear features and a partial set from the elements of the coherence matrix. Liang (2008) also investigated the performance of different texture features using neural network classifier. Bombruno (2008) demonstrated that the use of an appropriate texture distribution is useful to segment textured PolSAR images. Dabboor et al. (2008), also, combined the textural features in each scattering category obtained from the Freeman-Durden decomposition with the number of the scattering mechanisms from the entropy calculated from the Cloude-Pottier decomposition. in order to perform the segmentation process. Zhang et al. (Zhang, 2009) combined the scattering powers of MCSM (Multiple-Component Scattering Model) and selected texture features from Gray-level co-occurrence matrices using SVM (Support Vector Machine) classifier and neural network (Zhang, 2009). The objective of this paper is to evaluate the performance of texture modelling of polarimetric SAR images in land-cover classification by two steps scheme: the first step is Cloude and Pottier decomposition and the second one is markovian textural classification applied on decomposed images. For evaluation

2. POLARIMETRIC SAR CLASSIFICATION

purpose, the result is compared to a classification obtained

using Wishart classifier.

Many supervised and unsupervised classification methods have been proposed, such as methods based on the maximum likelihood (ML), artificial neural networks (NN), support vector machines (SVM), fuzzy methods, etc. An usual approach is to classify polarimetric SAR images based on the inherent characteristics of physical scattering mechanisms using decomposition theorems (Cloude, 1996; Touzi, 2004). Several decomposition techniques were proposed. These techniques are

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based on three principal approaches known as coherent methods, Huynen decomposition (Huynen, 1970) and non coherent methods. These methods split the scattering matrix into the sum of elementary scattering matrices, each one defining a deterministic scattering mechanism (Touzi, 2007). As we are dealing with texture which is a neighbourhood property, we choose to compare the textural classifier to a classifier based on incoherent decomposition. Indeed, non coherent decompositions permit to take into account the context, thus neighbourhood. For this purpose, we used whishart classifier. In fact, the characteristic decomposition of the Hermitian target coherency matrix allowed Cloude and Pottier to derive key parameters, such as the scattering type α and the entropy H, which have become standard tools for target scattering classification and for physical parameter extraction from polarimetric SAR data.

2.1 Textural Classifier

Image texture, defined as a function of the spatial variation in pixel intensities, is useful in a variety of applications and has been a subject of intensive study by many researchers. The texture parameter is extremely important for radar imagery interpretation, especially in terrain mapping. In fact, Radar image depends heavily on the scattering of ground objects and its textures/structures strongly vary with different objects. Many models have been employed in texture analysis including autoregressive model, Markov random fields (MRF), Gaussian random fields, Gibbs random fields, World model, wavelet model, multichannel Gabor model, fractal model, etc (Chellapa, 1993; Bader, 1995; Arivazaghan, 2003). In this study, we use a non parametric Markovian model that has been successfully applied to SAR image classification (Kourgli, 2009) and adapt its formulation to polarimetric images.

2.1.1 Texture model: Markov theory states that each pixel in an image has an independent local spatial property characterized by its surrounding neighbours. A discrete Markov field $\{X\}$ is defined on a 2-D lattice *S* with a neighbourhood structure N_S . Its global properties (Π) are controlled by means of local properties which are defined by local conditional probabilities (Derin, 1987; Li, 2000) The Markov property describes local conditional dependence of pixels image as:

$$\forall x \in \Omega, s \in S, \Pi_s (X_s = x_s / X_r = x_r, r \in S, r \neq s)$$

$$= P (X_s = x_s / X_r = x_r, r \in N_s)$$

$$(1)$$

Another attractive property of an MRF is that, by the Hammersley-Clifford theorem (Hammersley, 1971) an MRF can be characterized by a global Gibbs distribution that is usually defined with respect to cliques. A clique C is a particular spatial configuration of pixels, in which all its members are statistically dependent of each other:

$$P(x_s \mid x_r, r \in N_s) = \frac{\exp(-U(x))}{Z_s}$$
⁽²⁾

Where
$$U(x) = -\sum_{c \in C_s} V_c(x)$$
 is called energy and is

obtained by summing potential functions $V_C(x)$ while Z_S is a normalizing constant. A probability model is usually specified by a parametric probability distribution. The model is to be identified, in order to find best values for unknown parameters of the model for a given training texture. Due to usually complex mathematical form of texture distribution and because almost natural textures are quasi-stationary, parametric models fail to model them. Hence, we adopted an energy formulation defined by a Neighbourhood Likeness Measure (NLM) which is estimated between the neighbourhood N_S and all the neighbourhoods N_Y contained in the texture sample Y.

This measure is given by:

$$U(x) = NLM (N_{s}, N_{y \in Y})$$

$$U(x) = \frac{1}{card(N_{y})} \sum_{y_{r} \in N_{y}, x_{r} \in N_{x}} (y_{r} - x_{r})^{2}$$
(3)

Texture modelling can be performed in order to reproduce natural textures, but it can also be used as a tool for a classification or for a segmentation purpose.

2.1.2 Classification: The texture segmentation problem is the labelling of pixels in a lattice to one of texture classes, based on a texture model and the observed intensity field. Bayesian approaches, where maximum *a posteriori* (MAP) estimation is usually involved to image segmentation, have been proven efficient. In addition, we adopted the assumption presented in (Bouman, 1994) which states that the joint probability of a pixel in a window F_s can be approximated by the product of the neighbourhood probabilities over this window:

$$\Pi (x_s, s \in F_s) \approx \prod_{s \in F_s} P_s (x_s / x_r, r \in N_s)$$
⁽⁴⁾

As a combined use of physical scattering characteristics and statistical properties for terrain classification is desirable, we apply textural classification on Pauli decomposed vector. The Pauli vector, for a full polarimetric data, is given by:

$$\vec{K}_{P} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ 2S_{HV} \end{bmatrix}$$
(5)

The first element of the vector expresses odd bounce scatterer type such as the sphere, the plane surface or reflectors of trihedral. The second one is related to a dihedral scatterers or double isotropic bounce and the third element is related to horizontal and a cross polarising associated to the diffuse scattering or volume scattering.

Using the probability defined above and Pauli decomposition, we performed a classification scheme which is described as follows:

- Select from each texture image a sample.
- Scan the mosaic texture using a window sized *F_s* with a step of one pixel in the row and column directions, and calculate the joint probabilities defined by equation (4) for each sample in the three decomposed images
- The central pixel of the window considered will be assigned to the class maximizing the joint probabilities calculated.

2.2 Wishart classifier

In this work we are using the non coherent decomposition proposed by Cloude and Pottier. It is based on the coherency matrix calculated using the Pauli basis and given by (Cloude and Pottier, 1997):

$$\left[T\right] = \left\langle \vec{k}_{p} \cdot \vec{k}_{p}^{T} \right\rangle \tag{6}$$

This is a multilook 3x3 positive semi-definite hermitian coherency matrix where the superscript T denotes the matrix transpose, and < > indicates multilook averaging. The $\sqrt{2}$ on the term is to ensure consistency in the span (total power) computation. The eigenvectors and eigenvalues of the coherency matrix [T] can be calculated to generate a diagonal form of the coherency matrix which can be physically interpreted as statistical independence between a set of target vectors.

2.2.1 Entropy, alpha and anisotropy: The eigenvalues of [T] have direct physical significance in terms of the components of scattered power into a set of orthogonal unitary scattering mechanisms given by the eigenvectors of [T], which for radar backscatter form the columns of a 3 x 3 unitary matrix. Hence, we can write an arbitrary coherency matrix in the form (Papathanassiou, 1999):

$$\langle [T_3] \rangle = [U_3] [\Sigma] [U_3]^{-1} = \sum_{i=1}^3 \lambda_i \vec{u}_i \vec{u}_i^{*T}$$
(7)

where $[\sum]$ is a 3x3 diagonal matrix with nonnegative real elements:

$$[\Sigma] = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix}$$
(8)

 $[U_3] = [u1 u2 u3]$ is a unitary matrix, where u1, u2 and u3 are the three unit orthogonal eigenvectors

After eigen vector decomposition of the coherency matrix the entropy H, which is a measure of the randomness of the scattering process, is deduced from the eigen values as:

$$H = -\sum_{i=1}^{3} P_i \log_{3} (P_i)$$
⁽⁹⁾

where P_i are the probabilities obtained from the eigenvalues λ_i :

$$P_i = \frac{\lambda_i}{\sum\limits_{i=1}^{3} \lambda_i}$$
(10)

The entropy *H* represents the randomness of the scattering. H = 0 indicates a single scattering mechanism (isotropic scattering) while H = 1 indicates a random mixture of scattering mechanisms with equal probability and hence a depolarising target.

The parameter α is indicative of the average or dominant scattering mechanism. It describes the dominance of the scattering mechanism in terms of volume, double bounce or surface scattering types. The α angle is obtained from the α_i angles of each of the eigen vectors as follow:

$$\overline{\alpha} = \sum_{i=1}^{3} P_i \alpha_i \tag{11}$$

The anisotropy A is a parameter complementary to the entropy. It measures the relative scattering of the second and the third eigenvalues of the eigen-decomposition. It is given by:

$$A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3} \tag{12}$$

If the pair $H - \alpha$ plotted on a plane then they are confined to a finite zone. This plane is subdivided into eight zones characterizing different classes corresponding to different scattering mechanisms.

2.2.2 Classification: The basic scattering mechanism of each pixel of a polarimetric SAR image can be identified by comparing its entropy and parameters to fixed thresholds. The different class boundaries, in the H-alpha plane, have been determined so as to discriminate surface reflection (SR), volume diffusion (VD) and double bounce reflection (DB) along the α axis and low, medium and high degree of randomness along the entropy axis. When the anisotropy parameter is introduced, it allows the possibility to distinguish different clusters where the centers belong to the same H – α partition (Ouarzeddine, 2007).

The eight classes resulted from the H– α decompositions are used as training sets for the initialization of the unsupervised Wishart classifier. For a coherency matrix <Ti> of a pixel i of a multilook image (L-looks) knowing the class ω i, the Wishart complex distribution is given by:

$$p(\langle [T_i] \rangle | \omega_m) = \frac{L^{L_q} | \langle [T_{3i}] \rangle |^{L_{-q}}}{K(L,q) |V_m|^L} \exp\left(-Ltr\left(V_m^{-1} \langle [T_{3i}] \rangle\right)\right)$$
(13)

here
$$\Sigma_m = E\left(\langle [T_i] \rangle | \langle [T_i] \rangle \in \omega_m\right) = \frac{1}{N_m} \sum_{i=1}^{N_m} \langle [T_i] \rangle$$

 N_m is the pixel number of ω_m K(L,q) | is the factor of standardization given by :

$$K(L,q) = \pi^{q(q-1)/2} \prod_{i=1}^{q} \Gamma(L-i+1)$$
(14)

Where q=3 in the case of reciprocity (i.e., Shv=Svh), || and tr (.) indicate the determinant and the trace of the matrix respectively, and $\Gamma(.)$ is the gamma function.

A probabilistic measurement of the distance between the a coherence matrix of an unspecified pixel <Ti>, and the average coherence matrix Σ_m of the class candidate ω_m , is obtained using:

$$d\left(\left\langle \left[T_{i}\right]\right\rangle, \Sigma_{m}\right) = \ln\left(\left|\Sigma_{m}\right|\right) + tr\left(\Sigma_{m}^{-1}\left\langle \left[T_{i}\right]\right\rangle\right)$$
(15)

Mathematically, each coherency matrix of an individual pixel is assigned with the most likely class ω_m with the minimal distance, if and only if :

$$d\left(\langle \left[T_{i}\right]\rangle, \Sigma_{m}\right) \leq d\left(\langle \left[T_{i}\right]\rangle, \Sigma_{j}\right)$$
(16)

for all $\omega_m = \omega_n$.

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The clusters of the first itération are used us a training set for the second itération until a consequent result is obtained.

3. DATA USED

The data is related to the site of Obepfaffenhofen and is captured on May 2000. It is covering the southern part of Munich, Germany and an area that embraces about 1 Km^2 was chosen in this study. The radar used is the Aeos1 of the Ex private Aerosensing GmBH company. An airborne radar with the P band (72 cm). The SAR images are acquired in fully polarimetric mode and are of important value to supply information on the terrain type. An area of 600×600 pixels has been extracted for this study (Figure 1).



4. CLASSIFICATION RESULTS

From Wishat classification result, we selected six samples sized 12×12 pixels, three forest types (magenta, yellow and cyan), two for base area (blue and green), and the last represents built up area (red). First, we considered each image from Pauli vector decomposition apart and performed textural classification in each scattering category. The result obtained for each decomposed image is shown in Figure 2.a, 2.b and 2.c, while Figure 2.d is a colour composite of the three probability images before labelling.



Figure 2: The textural classification using Pauli images (a,b and c) and their colour composite (d)

The different classes are well segmented in all the three scattering channels. Indeed, the result obtained is interesting since all the classes are almost correctly recognized, however, some confusion occurs at the boundaries of different classes. These preliminary results show that the model texture is sensitive to the polarization (the classification results are different for each scattering type) and that the different scattering mechanisms have also been discriminated. The composite colour (Figure 2.d) of the different segmented decompositions provides a first classification that is interesting. In a second step, we classified the image on the basis of the three Pauli images simultaneously maximizing probability over the three images. The results are illustrated in Figure 3. We have reduced the classification result of Wishart classifier to the same number of classes. The polarimetric textural classification (Figure 3.b) appears consistent with the result obtained from Wishat classifier (Figure 3.c). We notice a large similarity for base area (in blue and in green) and built-up area (in red).

Figure 1: A colour composite of the test site using the Pauli basis.



Figure 3: A colour composite of the test site (a) using the Pauli basis decomposition, polarimetric classification (b : textural classification, c : Wishart-A- α classification) and an image extracted from google earth software of the test site

For a comparison purpose and to check the efficiency of our textural classification, we computed the classification percentage for each class (table 4) taking the Wishart classification result as a reference.

| Classes | Color+rate | |
|--------------------|------------|-------|
| Built-up | Red | 89.53 |
| Mixed forests | Cyan | 44.45 |
| Deciduous forests | Yellow | 86.86 |
| Bare soil | Blue | 47.73 |
| Grass and fields | Green | 91.56 |
| Coniferous forests | magenta | 68.28 |

Table 4: Classification percentage

While showing good rates for three classes (>86%), textural classification performs less better for the other samples. The weak rates obtained for bare soil (in blue) and mixed forests (in cyan) could be justified by a bad localization of the corresponding samples used in textural classification process. Furthermore, we give at Figure 3.d an optical image (Google Earth) of the same area. We can see that buit-up area (in red) has well identified by the textural classification, but some confusion occurs between decidious forests (in yellow) and built-up area. This gives a clear indication of how the classification algorithm has performed. Thus, textural modelling performed in every scattering type of Pauli decomposition makes good object discrimination of SAR polarimetric images

if samples are correctly chosen. This can be done, for example, by using H $-\alpha$ partition.

5. CONCLUSION

The different polarisations respond in different ways to the orientation and shape of the objects from which scattering takes place. It is obviously important to have tools that make full use of this information. The main purpose of this paper was to test object separability performance by using texture modelling in each scattering type. As the information in the fully polarimetric data can not be completely represented by one single feature, the combination of different polarimetric features incorporating spatial information seems to give interesting results. Indeed, textural modelling of polarimetric images provides a possibility to separate different classes and proves the texture features polarization dependence. It was shown that texture significantly contributed to land cover discrimination where backscattering coefficient could fail. Thus, our results confirm previous findings that texture incorporating can improve polarimetric images interpretation and help in land cover identification.

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