Object Based Analysis of Polarimetric SAR Data in Alpha-Entropy-Anisotropy Decomposition Using Fuzzy Classification by eCognition

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Abstract – **Polarimetric SAR data possess a high potential for classification of earth surface. Various publications demonstrate detailed analysis of soil and vegetation properties and characteristics of man made structures on selected examples. To ensure wider application of these developments, integration in commercial systems should be studied. Here, in a first approach, the object based image analysis eCognition is employed on alpha, entropy and anisotropy and the span of fully polarimetric L-Band SAR data of the German airborne sensor, E-SAR. We show that by using eCognition land cover classes can be conveniently assigned to the scattering classes and ambiguities can be resolved by geometric and context object features.**

1 INTRODUCTION

Radar polarimetry has a large potential for classification of earth terrain components. Compared to single polarization measurements a more detailed classification of objects is possible and the measurable attributes of objects can be expanded by bio-physical parameters. However these additional information extraction requires highly calibrated data and advanced signal processing. Promising algorithms extract dominant scattering mechanisms. Well known examples are Huynen and alpha-Entropy decomposition [2]. Recently the major role of anisotropy as extension to alpha-entropy decomposition was described by Pottier. All three parameters are roll invariant and are therefore well suited for operational usage.

Up to now, unsupervised Wishart classification in alpha-entropy or alpha-entropy-anisotropy feature space is employed to find clusters in the data or fuzzy rules combining alpha, entropy and first eigenvalue are created .

Fuzzy rule bases possess a high potential for model based classification of remote sensing data and especially polarimetric SAR data: a) vague relationships can be modelled, b) increased robustness with respect to varying parameters is provided, c) pixels belonging to several classes due to limited geometric resolution can be described more accurate and d) classification accuracy and stability are given for each classified pixel or object.

Fuzzy Logic is also used in eCognition as a main strategy to cope with the problems in remote sensing and to incorporate efficiently expert knowledge.

A major difference to the pixel based approach, used up to now for classification of polarimetric SAR data and usually for remote sensing data in general, is the object based approach of eCognition. Features are evaluated on objects instead of pixels, where objects consist of adjacent pixels with homogeneous values. Using these objects instead of pixels gives more meaningful features and allows geometric features, textural and – most important – also context features. Segments are not only built on one level, but on different scales leading to a hierarchy which can be used for classification as well: A typical advantage of humans is mimicked: scene analysis on multi-scales. Furthermore, eCognition provides convenient possibilities to fuse multi-sensor and ancillary data for efficient remote sensing information extraction.

2 POLARIMETRIC DECOMPOSITION IN ALPHA, ENTROPY AND ANISOTROPY

An important development in the understanding of how to best extract physical information from the classical 2x2 coherent backscattering matrix [*S*] has been achieved through the construction of the target vector $\underline{k}$ [2]:

$$\underline{k} = \frac{1}{\sqrt{2}}\left[S_{XX} + S_{YY} \quad S_{XX} - S_{YY} \quad 2S_{XY}\right]^T \tag{1}$$

In the analysis of experimental POLSAR data, we generally have access either to complete coherent scattering matrix data, or multi-look averaged Stokes matrix data. In either case, the local estimates of the coherency matrix can be formed using pixel averaging [2]:

$$\langle [T] \rangle = \frac{1}{N}\sum_{i=1}^{N} \underline{k}_i \cdot \underline{k}_i^{*T} = \frac{1}{N}\sum_{i=1}^{N}[T_i] \tag{2}$$

From this estimate, the eigenvectors and eigenvalues of the 3x3 hermitian coherency matrix <[*T*]> can be calculated. A parameterization of the eigenvectors of the 3x3 coherency matrix [*T*] has been introduced in [2]

$$\underline{u} = \left[cos a \quad sin a \, cos b \, e^{jd} \quad sin a \, sin b \, e^{jg} \right]^T \tag{3}$$

From this decomposition, three roll invariant parameters can then be defined: The entropy (H), the anisotropy (A) and the alpha angle ($\underline{\alpha}$) given by [2]:

$$H = -\sum_{i=1}^{i=3} P_i \, log_3(P_i), \quad A = \frac{P_2 - P_3}{P_2 + P_3}, \tag{4}$$

$$\underline{a} = P_1 a_1 + P_2 a_2 + P_3 a_3$$

where P_i are the probabilities defined from the eigenvalues λ_i of <[*T*]> [2].

These three roll invariant parameters have physical interpretations and details can be found in [2].

Here, alpha, entropy and anisotropy are calculated on L-Band full polarimetric data of DLR's SAR sensor, E-SAR. Testsite is Oberpfaffenhofen airfield. The calibrated data are delivered in slant range geometry. This ensures that data distribution is not altered and decomposition results would be correct also in rough terrain. In following studies geo-coding of decomposition or geo-coding of segmentation results will enable the envisaged fusion with already available geoinformation, (e.g. German ATKIS).

However, for this first study of eCognition's possibilities to segment and classify in alpha-entropy-anisotropy feature space, geo-coding was not necessary.

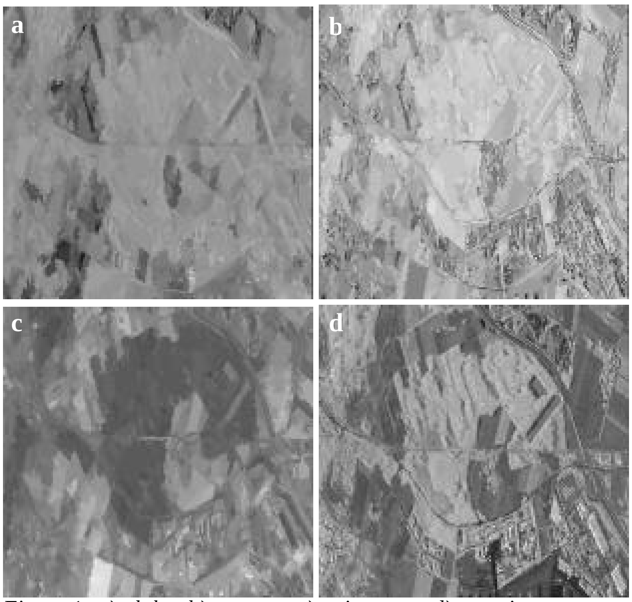


Figure 1: a) alpha, b) entropy, c) anisotropy, d) span image

3 MULI-SCALE SEGMENTATION WITH ECOGNTION

Segmentation by eCognition groups adjacent pixels with similar pixel values to segments, so called image objects. This process follows an optimization strategy, which minimizes the increasing heterogeneity for each segmentation step. The definition of heterogeneity can be adapted to considered application and data characteristic. It contains not only spectral measures but also form criteria. They are very helpful for larger objects and noisy data to get useful image objects for geo-information systems, which base usually on generalized regularly shaped polygons. The patented optimisation process of eCognition ensure segmentation results independent of the pixels' sequence.

In this study four input layers are used in eCognition: 1) span of the image, 2) alpha, 3) entropy and 4) anisotropy. For initial segmentation only the span of the image is used, for the following high level segmentations, alpha, entropy and anisotropy are used as well.

Using minimum number of layers for initial segmentation reduces computational requirements significantly, because the large number of all pixels has to be considered. Reduction of computational requirement becomes important especially if other frequencies and ancillary data should be simultaneously used for further advanced applications.

Of course, also in the initial segmentation layer all heterogeneities, which can be of any importance should be covered. This is the case for the polarimetric power in the data set, represented by the span of the image. This assumption is used by Lee's polarimetric speckle filter [4] and also discovered as sufficient for multipolarisation, multifrequency analysis of SAR data [3]. Table 1 gives an overview on the selected segmentation settings.

Level	layers	heterogeneity		object number	Average obj. size in pixels
		color	shape		
1	span	0.9	0.1	80523	54
2	span alpha entropy anisotropy	0.8	0.2	19086	223
3		0.8	0.2	7787	557
4		0.8	0.2	3224	1345
5		0.6	0.4	775	5596

Table 1: Segmentation settings, resulting object number and average size.

4 RULE BASE DEVELOPMENT

After this multi-scale segmentation image objects are available on 5 levels. Though the average object size on level 3 is 557 pixels, it still preserves small objects with high contrast as the corner reflections of buildings. Thus it provides a high flexibility for this study with no distinct final application.

Aggregation of pixels to image objects has two major advantages, 1) only a reduced number of class assignments have to be performed and 2) features – only available or more meaningful for objects – can be evaluated for classification.

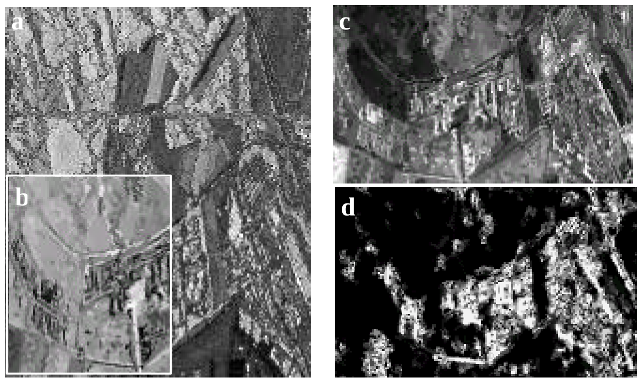


*Figure 2: Feature view: a) layer mean and segment borders on level 4, b) ratio of entropy to all other channels (level 3), c) user defined: (1-H)*A, d) relative border to man made targets*

For example, the spectral features *mean* and *standard deviation* base on statistic which is more relibale on larger areas. Form features, as *size, length/width* and *orientation* are only available for image objects and carry useful information. Other features are texture and context, e.g. *number of neighbours* or the *common border length* with a distinct class. Neighbourhood itself can be defined by parameters to take into account as well spatially close correlations or correlation over a larger spatial extension. Recent developments allow free definition of features to ensure high flexibility for many applications. For example, the polarimetric feature (1-H)*A (compare Figure 2)

The primary rule base follows Pottier's strategy [2]. First, the image is divided into regions with low and high anisotropy, these regions are subdivided in regions with low, medium and high entropy and again split in low, medium and high alpha areas. Already the first class assignment in low and high anisotropy shows the high potential of this parameter.

The fuzzy set "very low backscatter" was introduced to separate regions with low signal-to-noise ratio and thus less reliable phase information and resulting in less meaningful polarimetric decomposition.

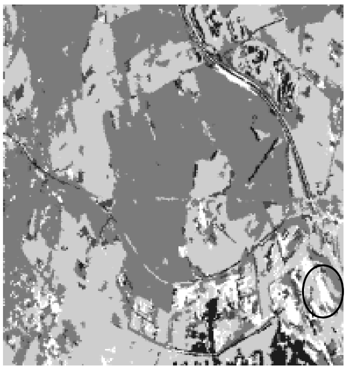
Based on these scattering classes the fuzzy rules allow to decide between 8 types of vegetation, 4 types of forest, and artificial objects like buildings, streets and places.

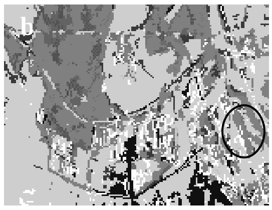
All types of forest show low anisotropy and either high (forest type 3) or medium entropy. Alpha is used to distinguish between forest types 1, 2 and 4.

Unfortunately some artificial object's have also – like forest 1 and 2 - low anisotropy, medium entropy and high or medium alpha. Only class related features are able to separate: The following fuzzy rule is applied: "If objects assigned to forest 1 or 2 and if they have a common border with image objects assigned to one of the man made targets objects classes, these forest object's are aggregated to the neighbouring man made targets". This rule models to some extent the human's efficient possibility to resolve ambiguities using context information.

Veg. 1,2 and 3 are areas with low anisotropy and medium entropy. Alpha is used to distinguish between these classes. Medium vegetation (veg. 6) is similar to forest 2, but polarimetric power is significantly smaller. Veg. 7 is characterized by low anisotropy, medium entropy and medium alpha. However, this class is mixed with areas close to man made targets without vegetation These two land cover classes can be efficiently separated using the object's size: Only objects larger than 600 pixels ($\approx$ 600 m^2) are assigned to veg. 7. Veg. 4,5 and 8 are dominated by surface scattering with low alpha and low (5, 8) or medium entropy (4). Anisotropy separates veg. 5 from veg. 8.

Further rules are used to extract streets and the runway of Oberpfaffenhofen airfield. All vegetation objects, all forest objects, man made targets and remaining objects are grouped for the classification shown in figure 3.





dark: *street and runway*
light grey: *low to medium vegetation*
grey: *forest 1 and 2*
bright: *man made targets*

Figure 3: Classification using eCognition's rule base, a) with and b) without class related features. In b) buildings are misclassified as forest.

5 CONCLUSIONS AND DISCUSSION

The new approach of fuzzy, object oriented rule based classification by eCognition allows to model the relationship between most of the different scattering classes detectable in alpha-entropy-anisotropy feature space and basic land cover classes. Additional use of geometric and context features reduces ambiguities. Aggregation in semantic groups gives flexible results for various applications. Thus the high potential of alpha, entropy and aniso tropy to extract information from polarimetric SAR data can be significantly extended. Future evaluations have to proof, if the use of backscatter power reduces the transfer of the rule base to other data sets. We don't expect this, because the span was only used with flat membership functions to allow large parameter variations.

In future – if detailed ground measurements are available - further rule base refinement will allow to map the various vegetation and forest classes found by classification to real land cover classes with distinct bio-physical parameters.

6 REFERENCES

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