Hierarchical Supervised Classification of Multi-Channel SAR Images

Dirk Borghys, Yann Yvinec, Christiaan Perneel, Aleksandra Pizurica and Wilfried Philips

***Abstract*— This paper describes a new method for supervised classification of multi-channel SAR data. Multi-channel SAR data (multi-frequency, polarimetric, interferometric) offer a multitude of different types of information that can be used, among others, as input features for classification. This paper proposes a way to combine this information into a supervised classification scheme using statistical methods. Because the different input features have very diverse statistical distributions classic feature selection and classification methods are inadequate. We therefore developed a method based on logistic- and multi-nomial regression. These two statistical methods are less dependent on the statistical distribution of input data and which combine feature selection with the search for an optimal combination of features. The classification method proposed here is supervised: a number of classes was defined and examples of each class were gathered. These were divided into a learning and a validation set. The proposed classification method is hierarchical: classes which are difficult to distinguish are grouped. In a first step these groups are separated from each other. In sub-sequent steps, the groups are further sub-divided. The separation between different groups or classes is based on logistic and multi-nomial regression, which find the best combination of features to make the separation and at the same time perform a feature selection. The combination results in a "detection image" for each class. Majority voting is used to combine the detection images into a classification map. The method is applied to a project on humanitarian demining. For that project a set of multi-channel SAR data, including polarimetric and dual-pass interferometric data at different frequencies, was acquired using the E-SAR system of the German Aerospace Centre (DLR). The aim was to classify different land-cover classes that are relevant for deciding whether a region is potentially mined or not. Classes typically include "Abandoned Agricultural Land", "Used Fields", etc. The classes were defined by interviewing experts of a Mine Action Centre. A ground survey mission collected the necessary ground-truth information for each class. Results of the proposed classification method are shown and evaluated.**

***Index Terms*— Logistic Regression, Multi-Channel SAR Images, Multi-Nomial Regression, Supervised Image Classification**

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I. INTRODUCTION

This article presents a new method for supervised classification of multi-channel SAR data. The method was applied to a project on humanitarian demining. A set of multi-channel SAR data, including polarimetric and dual-pass interferometric data at different frequencies, was acquired using the E-SAR system of the German Aerospace Centre (DLR). The images from different bands (P, L , C and X-band) cover the same region but each band has a different spatial resolution. Geocoding information was also provided. The relevant land-cover classes were defined by interviewing experts of a Mine Action Centre. A ground survey mission collected the necessary ground-truth information for each class.

For classification of polarimetric SAR images, several unsupervised approaches have been proposed, based on various polarimetric decomposition methods [1]. The most used method is the decomposition of Cloude and Pottier [2]. In this method the polarimetric information is converted into three parameters (entropy H, α-angle and Anisotropy A) to which the authors have associated an elegant physical interpretation. They subdivided the feature space formed by the three parameters into regions that correspond to distinct scattering behaviours. However, the exact borders of these different regions depend on many factors. Different methods were suggested to make these borders flexible. In [3] the samples in the feature space are regrouped based on the complex Wishart distribution. In [4] a supervised classification method based on neural networks and fuzzy logic is used to learn the class borders from the available learning samples. The advantage of the approach proposed in [4] is that other input features can be easily added in order to increase the discrimination ability of the classification. In [4] the largest eigenvalue (λ_1) of the polarimetric coherence matrix and the interferometric coherence ρ are added.

We recently developed [5] an approach based on logistic regression, which considers each class separately and tries to distinguish it from all others by combining the input features into a non-linear function, the logistic function. The method allows adding features easily. Moreover, for each class a "detection image", with a well-defined statistical meaning, is obtained. The value at each pixel in the detection image for the learning set represents the conditional probability that the pixel belongs to that class, given all input features. The detection images are interesting as such for the human photo interpreters working at the Mine Action Centre. The logistic regression was carried out using Wald's forward, step-wise method. In this method, at each step, the most discriminant feature is added and the statistical significance of adding it to the model is verified. The method thus implicitly performs a feature selection.

In order to improve the developed method, in this paper we introduce a hierarchy in the classification: classes that are easily distinguished are detected first and sub-sequent steps of the classification only consider remaining classes. Furthermore we replaced the logistic regression by a multi-nomial regression for distinction between more than two classes or groups of classes. Multi-nomial regression takes into account constraints between all classes involved in the classification step and gives better results.

II. Input Data

A. Overview of the SAR data set

The method was applied to a project on humanitarian demining for which the German Aerospace Center DLR acquired E-SAR data at 4 different frequencies. P-band and L-band are full-polarimetric, dual-pass interferometric, while due to flight time limitations, for C- and X-band only VV-polarisation is available. All data were delivered as SLC data and geocoded amplitude data. They were acquired from parallel flight paths and cover approximately the same region. However the pixel spacing in the SLC data of different bands is not the same. Together with the data, we therefore also received geocoding matrices that enable us to extract polarimetric and interferometric information using the SLC data and geocode the results afterwards.

B. Derived feature set

From the input SAR data several input features were derived:

- Radiometric information: values in the speckle reduced log-intensity images of each frequency and each polarisation (8 features). The speckle reduction method [6] combines a context-based locally adaptive wavelet shrinkage and Markov Random Fields to limit blurring of edges, by incorporating prior knowledge about possible edge configurations.
- Polarimetric information: provided by the parameters of the Cloude decomposition [2] (H, α -angle and λ_1). λ_1 is the largest eigenvalue of the polarimetric coherence matrix. These are available in P- and L-band, resulting in 6 features.
- Interferometric information: From the pairs of dual-pass interferometric images the interferometric coherence (ρ) is calculated. This results in 2 features (ρ_L and ρ_P)
- Spatial information: Some basic spatial information is included in the feature list. It consists of the results of a bright and a dark line detector [7]. The line detector uses a multi-variate statistical test for detecting line structures and is applied on the 8 speckle reduced, geocoded, log-intensity images. These input channels are treated by the detector as a single vectorial input and a single result is obtained for the dark lines and another for the bright lines (2 features).

The polarimetric and interferometric features were determined on the slant-range SAR data and then geocoded. The speckle reduction was applied on the geocoded images. In total 18 input features are available.

C. Ground-truth

A ground survey mission was organised to acquire ground truth, i.e. the relevant classes of land cover in the scene were determined and for each of them examples were given. The ground-truth objects were then divided into a learning set and a validation set. Both sets contain around 200 objects from the test-site. The learning set was used to determine the parameters of the logistic and multi-nomial regression at different stages of the classification. Table I shows the classes used for the learning set. For the validation set some classes are merged because their distinction does not give relevant information to the deminers. The different types of crops (C3, C4 and C5) are merged into a class ”Fields in use with vegetation” and class C9 (forests) is merged with C11 (hedges and shrubs). The reason to keep them separate for the learning step is to avoid complicating the classification task by having heterogeneous classes.

TABLE I
Classes used in the learning set

Nr	Name	Nr	Name
C1	Abandoned Land	C7	Roads
C2	Fields in use without Vegetation	C8	Pastures
C3	Fields of Barley	C9	Forests
C4	Fields of Wheat	C10	Water
C5	Fields of Corn	C11	Hedges/Shrubs
C6	Residential area	C12	Radar Shadows

III. Statistical Methods

The classification scheme uses two statistical methods: logistic regression and multi-nomial regression. Both methods offer a way to combine the different input features while at the same time performing a feature selection.

A. Logistic Regression

Logistic regression [8] is developed for dichotomous problems where a target class has to be distinguished from the background. The method combines the input parameters into a non-linear function, the logistic function, defined as:

$$p_{x,y}\left(target \mid \overrightarrow{F}\right) = \frac{exp\left[\beta_o + \sum_i F_i(x,y)\beta_i\right]}{1 + exp\left[\beta_o + \sum_i F_i(x,y)\beta_i\right]} \qquad (1)$$

$p_{x,y}\left(target \mid \overrightarrow{F}\right)$ is the conditional probability that a pixel (x,y) belongs to the considered class (target class) given the vector of input features ($\overrightarrow{F}$) at the given pixel. The logistic regression (i.e. the search for the $\beta_i's$) was carried out using Wald's forward step-wise method. In this method, at each step, the most discriminant feature is added and the significance of adding it to the model is verified. This means that not all features will necessarily be included into the model. The logistic regression thus gives an optimal combination of a subset of input parameters and also provides an objective method for determining the impact on the classification of adding each parameter to the model. Applying the obtained combination to the complete image set, a new image - a “detection image” - is obtained, in which the target class under consideration is bright and the background dark.

B. Multi-Nomial Regression

Multi-nomial regression is very similar to logistic regression. It is used to distinguish more than two classes. In the multi-nomial regression all classes are considered at the same time. The last class is the so-called baseline class (j^*). This time a set of combinations of input features is found such that

$$p_{x,y}\left(Class_j \mid \overrightarrow{F}\right) = \frac{exp\left[\beta_{o,j} + \sum_i F_i(x,y)\beta_{i,j}\right]}{1 + \sum_{k \neq j^*} exp\left[\beta_{0,k} \sum_i F_i(x,y)\beta_{i,k}\right]} \tag{2}$$

for the non-baseline classes, where the sum in the denominator is over all classes, except the baseline class, and:

$$p_{x,y}\left(Class_{j^*} \mid \overrightarrow{F}\right) = \frac{1}{1 + \sum_{k \neq j^*} exp\left[\beta_{0,k} \sum_i F_i(x,y)\beta_{i,k}\right]} \tag{3}$$

for the baseline class.

IV. Image Classification Method

A. Classification Tree

Fig. 1 presents an overview of the classification tree used in this project. At the first level logistic regression (LR) is used to separate the group of “Forests and Hedges” from all other classes. Forests and hedges are separated from each other using again logistic regression. For separating the other classes multi-nomial regression (MNR) is used. The advantage of the hierarchical approach is that at each level the full discriminative power of the input features is focussed on a sub-problem of the classification.

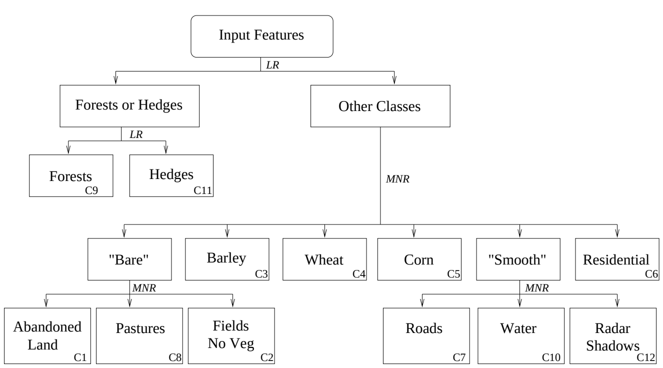

Fig. 1. Overview of the classification tree.

B. Majority voting

When the logistic or multi-nomial regression is applied to all pixels of an image set, a “detection image” for the considered class(es) is obtained. The pixels in these detection images represent the conditional probability that the pixel belongs to the class given all input features. The detection images are combined into a classification using majority voting, i.e. in a neighbourhood (typically 3x3) of each pixel the sum of conditional probability for each class is determined and the pixel is assigned to the class corresponding to the highest sum. Note that this majority voting has to be performed at each level of the tree and the derived decision is used as a mask for the classification on the next level. Although both methods give conditional probabilities it is not possible to compare probabilities obtained at different levels of the tree.

V. Results and Discussion

In Figure 2 the results of the method are shown: figure A is the polarimetric L-band E-SAR image after speckle reduction of a part of the test site, in fig. B. the detection image for the class “Abandoned Land” is shown and Fig. C is the final classification result. Using the validation set a confusion matrix was calculated (table II). From this matrix statistics were calculated for the validation and also shown in the table. Besides the conditional kappa coefficients (κ) [9] calculated per class, the user’s and producer’s accuracies (UA and PA) are also given in table II. The UA is the ratio of the number of pixels correctly classified as a given class i to the total number of pixels belonging that class, i.e. the diagonal element of the confusion matrix divided by the sum of the elements in the column. This is related to the probability of detection. The PA is the complementary, i.e. the ratio of the number of pixels correctly classified as a given class i to the total number classified as that class. This is related to the probability of false alarms.

$$UA(C_i) = \frac{Conf(i,i)}{\sum_{j=1}^{N} Conf(i,j)} \tag{4}$$

$$PA(C_i) = \frac{Conf(i,i)}{\sum_{j=1}^{N} Conf(j,i)} \tag{5}$$

where N is the number of considered classes. A high UA and a low PA means that most of the pixels belonging to the considered class have been correctly classified but that there are many false alarms.

Table II shows that good results are obtained for most classes. An important exception is C2 (Fields in use without vegetation). This class seems to be heavily confused with C8(pastures). Most pixels belonging to class C2 are classified as C8, while some of the pixels belonging to C8 are classified as C2. This explains the low PA for C2 and the low UA for C2 and C8. The relatively low value for the PA of C6 (residential areas) is probably due to the fact that these regions are not homogeneous for a SAR. The residential areas indeed include buildings, with double bounce reflectors and shadow areas as well as empty spaces between the buildings that can contain vegetation or asphalted surfaces. The introduction of textural features might reduce this problem. The low UA for roads (C7) is due to majority voting. While the majority voting is useful for region-like objects, it presents problems for narrow linear features. A more intelligent generalisation method should be used as the final step in the classification. If the majority voting would be replaced by a context dependent method such as Markov Random Fields (MRF) [10], [11], it is expected to improve the results for the linear objects. This will be investigated further. Note that most of the river

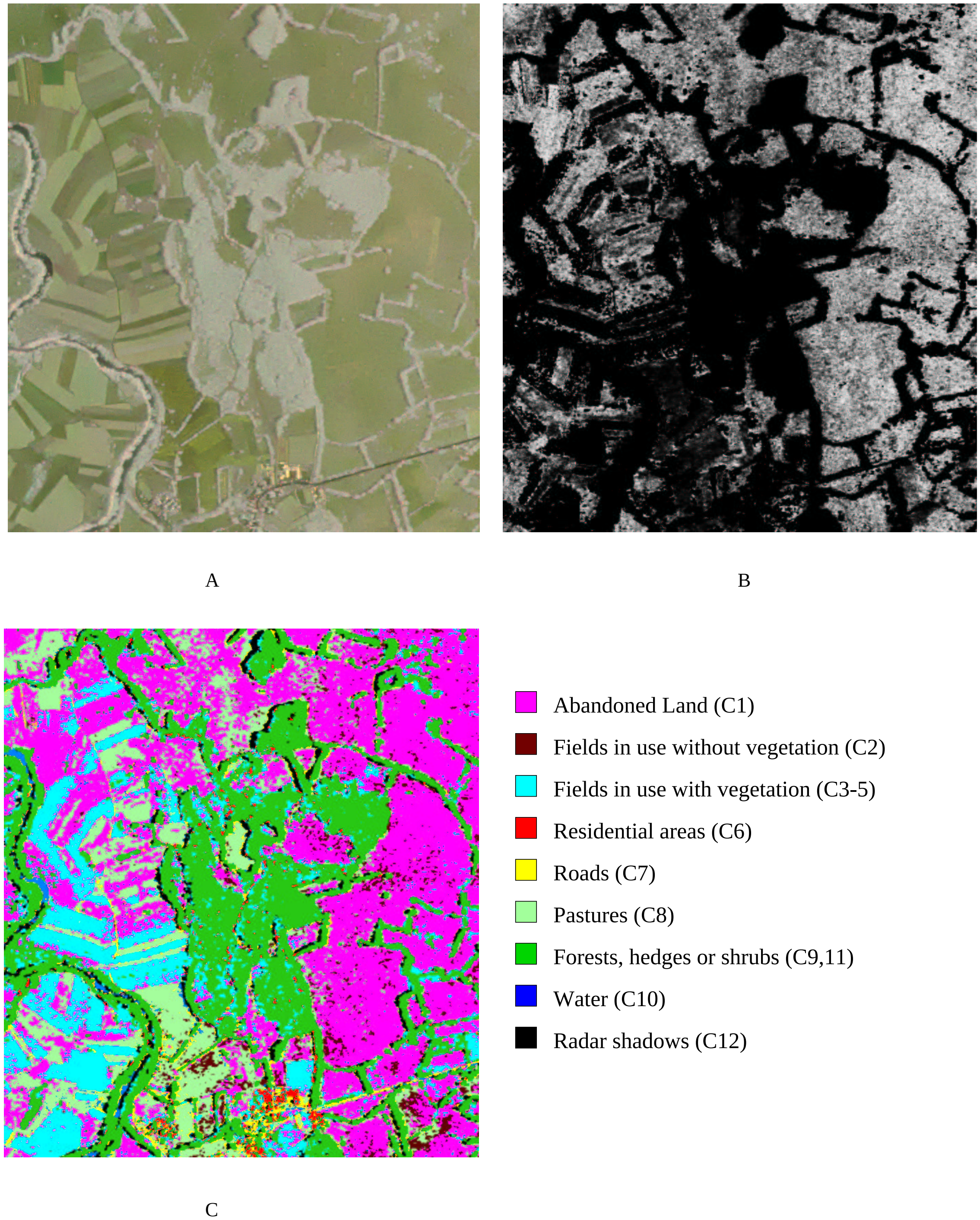

Fig. 2. Results of the method: A: part (1.3km $\times$ 1.5 km) of the speckle reduced polarimetric L-band image (R:HH, G:HV, B:VV) ©DLR, B: "detection image" for abandoned land, C: classification results

at the left of the image has been classified as shadow. This was expected because the river is bordered by trees and the radar look direction is from right to left. It does not influence the confusion matrix because both learning and validation set were constructed in order to avoid selecting shadow regions. However, for the creation of a land-use map it would be interesting to "infer" the presence of the river in the linear region classified as shadow. This requires spatial contextual reasoning and will also be explorer further.

VI. Conclusions

This paper presents a new method for supervised classification of multi-channel SAR images. The approach is hierarchical and feature-based. Various features were used that represent radiometric, polarimetric, interferometric and spatial information. The proposed classification method is hierarchical: classes which are difficult to distinguish are grouped. In a first step these groups are separated from each other. In sub-sequent steps, the groups are further sub-

TABLE II

CONFUSION MATRIX, UA, PA AND κ- COEFFICIENTS OF FINAL RESULTS

Confusion Matrix		Classification Classes									PA(%)
		C1	C2	C3-5	C6	C7	C8	C9,11	C10	C12	
Validation Set Classes	C1	**42617**	9003	1237	1	300	14355	432	114	181	62.45
	C2	2488	**1080**	1236	201	993	10651	5575	320	31	4.78
	C3-5	8141	119	**24197**	295	136	3815	4271	127	93	58.74
	C6	7	72	769	**1779**	528	67	1810	2	346	33.07
	C7	26	36	75	105	**639**	96	131	140	119	46.74
	C8	1219	7107	277	0	665	**12461**	480	68	56	55.80
	C9,11	903	60	2103	179	261	277	**23616**	210	479	84.08
	C10	44	8	67	5	152	3	345	**3114**	591	71.93
	C12	36	17	488	60	102	98	1411	354	**4270**	62.46
UA(%)		76.81	6.17	79.47	67.77	16.92	29.79	62.03	69.99	69.25	
κ		0.4807	-0.0433	0.5134	0.3218	0.4572	0.4413	0.8034	0.7130	0.6127	

divided. The separation between different groups or classes is based on logistic and multi-nomial regression. Both methods combine feature selection with the search for the classification function and result in detection images for each class. These are then combined using majority voting to obtain the final classification result.

The method is applied to a project on humanitarian demining where extensive ground-truth has been acquired for both learning and validation. The results are validated using statistical measurements on the obtained confusion matrix. Most classes are correctly classified. A noteworthy exception is the class "fields in use without vegetation" which is highly confused with the class "pastures". The input features do not contain information that allows to distinguish these two classes. For linear objects it is likely that the results can be further improved by replacing the majority vote by a MRF in the classification scheme. This possibility will be investigated further.

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