Supervised Feature-Based Classification of Multi-Channel SAR Images Using Logistic Regression

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Abstract

This paper describes a new method for supervised classification of multi-channel SAR images. For 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 aim was to try and classify a large number of different landcover 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 Center. A ground survey mission collected the necessary ground truth information for each class. This ground truth was divided into a learning and validation set. The proposed method combines all available information into a supervised, feature-based classification scheme. The input features include amplitude information after despeckling, results of polarimetric decomposition and interferometric coherence. The different parameters have diverse statistical distributions, it is thus not possible to use standard statistical techniques (e.g. factorial analysis) for reducing the feature space. Therefore a classification method based on logistic regression, was developed. The method considers each class separately and tries to distinguish it from all others by combining the input parameters into a non-linear function. Only features that have a statistically significant contribution to the discrimination of the given class are taken into account. The method results in a detection image for each class. These are combined into a classification map using majority voting. Classification results are evaluated using confusion matrices based on the validation set.

1 Introduction

This article presents a new method for supervised classification of multi-channel SAR data. The method was applied for a project on humanitarian de-mining[1]. 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. 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 landcover classes were defined by interviewing experts of a Mine Action Center. A ground survey mission collected the necessary ground truth information for each class.

For classification of POLSAR 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 sub-divided the feature space formed by the three parameters into regions that correspond to distinct scattering behaviour. 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 are added.

We propose here 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

[1] SMART: Space and airborne mined area reduction tools, funded by the EC, project nr. IST-2000-25044

function. The method allows to easily add features. Moreover, for each class a “detection image”, with a well-defined statistical meaning, is obtained. For the learning set the value at each pixel in the detection image represents the conditional probability that the pixel belongs to that class, given all input features. The detection images are in se interesting for the human photo interpreters working at the Mine Action Center.
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 performs implicitly a feature selection.
The "detection images" of the different classes are fused using a majority vote.

2 Input data

2.1 Overview of the SAR data set

For this project the German Space Agency DLR acquired E-SAR data at 4 different frequencies. P-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 one to extract polarimetric and interferometric information using the SLC data and geocode the results afterwards.

2.2 Derived feature set

From the input SAR data several input features were derived. The first ones consist of the value in the speckle reduced log-intensity images. The used speckle reduction method 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 [5].
In order to capture the polarimetric information, the parameters of the Cloude decomposition (H, α-angle and λ_1) are used. From the pairs of interferometric images the interferometric coherence (ρ) is calculated. The polarimetric and interferometric features are available for P-and L-band, which results in 8 parameters. Their values were rescaled to unsigned bytes using their physical limits.
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.

2.3 Ground truth

Twelve classes were defined for the project. A ground survey mission was organised to acquire ground truth, i.e. examples for each class.

Table 1: Landcover classes defined for the project

C1	Abandoned land	C7	Roads
C2	Fields without Veget.	C8	Pastures
C3	Fields of Barley	C9	Forests
C4	Fields of Wheat	C10	Water
C5	Fields of Corn	C11	Hedges/Shrubs
C6	Residential areas	C12	Radar Shadows

The ground truth objects were then divided into a learning set and a validation set. Both sets contain around 200 objects for each test-site. The parameters of the logistic regression were calculated using the learning set. The classes in the table are the classes for the learning set. For the validation set some classes are merged because their distinction does not give relevant information to the deminers. C3, C4 and C5 are merged into a class “Fields in use with vegetation” and C9 is merged with C11.

3 The classification method

Because the different input features have very diverse statistical distributions, classical methods for feature selection cannot be used. Therefore we developed an approach based on logistic regression (LR), which allows to combine feature selection and the creation of the classification function. Each class is considered separately and logistic regression is used to find a combination of input features that discriminates that class from all others based on the learning set.

3.1 Logistic regression

Logistic regression [6] offers a way to combine the different features while at the same time yielding a measure of their respective discriminative power. LR combines the different input features using a logistic function:

$$P_{x,y}(C_i \mid \vec{F}(x,y)) = \frac{e^{b_o + \sum_i b_i F_i(x,y)}}{1 + e^{b_o + \sum_i b_i F_i(x,y)}}$$

where $\vec{F}(x,y)$ is the vector of input features at pixel x,y, C_i is the class under consideration and the b_i's are the weights attributed by the logistic regression for that class to each feature.
The LR was carried out using Walds forward method. This is an iterative method and at each step the most discriminating feature is added and the statistical significance of adding it to the model is verified. This means that the creation of decision surfaces for the classification is combined with the feature selection.

3.2 The majority vote

When the logistic function for a given class is applied to all pixels of an image set, a detection image for the considered class is obtained. 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.

4 Application of the method

For each class a “target class” was created composed of all available samples of that class. The background class consists of samples from all other classes. Logistic regression gives the best results when the number of target and background samples is equal, these other classes were thus randomly sub-sampled. Table 2 presents the parameters that were found by the logistic regression. The table illustrates which features are used for distinguishing each class from the others, e.g. for detecting forests (C9), only 5 features are used.

Table 2: Parameters b_i found by the logistic regression

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
b_0	-2.06	-11.75	-87.30	-105.42	-20.94	-16.03	-1.32	-17.38	-170.44	67.02	-25.14	-11.21
L_{HH}	1.981	0.571	-2.580		0.804	0.449	-3.094	0.693		-2.705		2.193
L_{HV}					1.367				6.762		1.149	
L_{VV}			6.455	-1.080	0.590	-1.719	-1.973	0.696	4.882	-1.872	1.234	1.342
P_{HH}	0.482		0.901	-0.973	-1.678	1.743	1.707	1.052		-2.641		
P_{HV}	-2.135	-0.290		1.966		0.640	0.510			1.376	-0.701	
P_{VV}	-1.169		1.806	2.888	-0.355	-0.924	0.786				-1.593	1.510
C_{VV}	1.263	1.009	-2.912	2.631	0.467		-0.951	0.953			0.479	-1.772
X_{VV}	-0.628	0.779	3.557	3.384		0.504	2.218				-1.483	-2.706
ρ_L	0.019		0.048	0.045	0.031	0.041	0.011	-0.016	-0.163	-0.038	0.032	
ρ_P		-0.012		0.036	-0.010	-0.017	-0.009	0.007			0.047	0.025
H_L		-0.023	0.030		0.022	-0.010	0.019	-0.062	0.306		0.058	0.025
α_L		-0.012	-0.057	-0.012		0.010	0.021	0.010			0.036	
H_P	-0.021					0.017		-0.016		-0.025	-0.010	0.020
α_P			-0.031				-0.016	0.011				-0.019
λ_L	-0.008	-0.057		-0.106	-0.021		0.051	-0.044			0.033	-0.067
λ_P	-0.015		-0.059			0.024	-0.049	-0.031	-0.055	-0.108		-0.031

5 Results and discussion

In Figure 1 part of the L-band E-SAR image of one of the test sites is shown. Figure 2 shows the detection image for one of the classes, i.e. abandoned land Figure 3 shows the results of the classification. The colors of the classes are the ones used to for the class numbers in Table 1. Table 3 shows the results of the validation. Using the validation set a confusion matrix was calculated. The values in the table are statistics calculated from the confusion matrix. The κ is the Kappa-coefficient [7] calculated per class. UA is the *user's accuracy* and relates the proportion of pixels classified as a given class to the number that really belong to that class, i.e. diagonal element of the confusion matrix divided with the sum of the elements in the column. The *Producer's Accuracy* (PA) is the complementary:

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

The PA is thus linked to the probability of false classifications for a class while the UA is related to the probability of correct classification. Roads give very bad results in the classification. This is because they are too narrow to detect using a pixel-wise classification. Examination of the confusion matrix shows that fields without vegetation and pastures are confused which explains the low values in the table. For water the low value can be explained by the fact that a river bordered by trees was indicated in the ground truth. This means that many pixels were classified as shadows. The other classes show a good classification result (κ, PA and UA > 0.4). For residential areas the PA is very high while the UA is low. This is to the fact that the detection overestimates their size.

Figure 1: L-band E-SAR image (R.G.B=HH,VV,HV)

Figure 2: Detection Image for C1 (Abandoned Land)

Table 3: Objective validation results showing Kappa coefficient, producer's and user's accuracy

Cl	κ	PA	UA	Cl	κ	PA	UA
C1	0.47	0.62	0.59	**C8**	0.25	0.31	0.008
C2	0.34	0.41	0.37	**C9,11**	0.69	0.74	0.31
C3-5	0.49	0.60	0.40	**C10**	0.33	0.34	0.49
C6	0.75	0.76	0.20	**C12**	0.56	0.59	0.62
C7	0.05	0.05	0.37				

6 Conclusion

A new method for supervised classification of multichannel SAR data was proposed. The method detects each class separately using logistic regression and builds the classification map using majority voting. Most classes are correctly detected. Pastures and fields without vegetation are confused. Problems remain also for roads and rivers. These problems can probably be solved by combining the classification with the results of a detector for linear objects. This idea will be explored further.

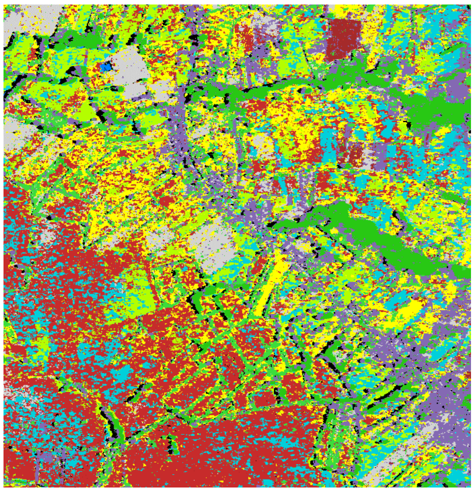

Figure 3: Classification Image

7 Literature

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