Supervised classification of multi-channel high-resolution SAR data

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Keywords: SAR, image classification, logistic regression, supervised classification

ABSTRACT: Many methods have been proposed in literature for the supervised classification of multi-channel (polarimetric and/or multi-frequency) SAR data. Most are based on the extraction of a set of features from the original SAR data. In this paper we examine the influence of these features on the results of the classification in a quantitative manner. A set of multi-channel (P, L, C and X band) SAR data was acquired by an airborne system over a site in Southern Europe. A ground-truth mission defined the classes for learning and validation. A feature-based classification method, based on logistic regression, is used for detecting each of the classes. Logistic regression combines the input features into a non-linear function, the logistic function, in order to distinguish that class from all others. For each class a "detection image", with a well-defined statistical meaning, is obtained. The logistic regression is performed using a step-wise method in which at each step, the most discriminating feature is added to the selected feature set, but only if its addition contributes significantly to the detection. The logistic regression thus also performs a feature selection. Moreover, logistic regression allows to combine input data with very diverse statistical distributions.
The main aim of the current paper is to investigate the usefulness of each feature for the detection of the different classes.

1 INTRODUCTION

This article presents a method for supervised feature-based classification of multi-channel SAR data and examines the influence of the different features on the classification performance. The presented classification method was applied in a project on humanitarian demining. Relevant land-cover classes were defined by the experts of a Mine Action Center. A set of multi-channel SAR data, was acquired using the E-SAR system of the German Aerospace Center (DLR). A ground survey mission collected the necessary ground truth information for each of the defined classes.
For classification of polarimetric SAR (POLSAR) images, several approaches have been proposed, based on various polarimetric decomposition methods (Cloude & Pottier 1996). The most used method is the decomposition of Cloude and Pottier (Cloude & Pottier 1997). 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. Different classes correspond to different sub-spaces in the H, A, α space. In (Hellmann 2000) a supervised classification method based on neural networks and fuzzy logic is used to learn the class borders of these sub-

spaces from learning samples. In this approach other features can be easily added in order to increase the discrimination ability of the classification. Hellmann adds the largest eigenvalue (λ_1) of the polarimetric coherence matrix and the interferometric coherence ρ to the feature set. In (Lee et al. 1999) a supervised classification is proposed based on the complex Wishart distribution of the polarimetric covariance matrix. This method is regarded as the recommended method for supervised classification of polarimetric SAR data (Rodriguez et al. 2003). The method can also be used for multi-frequency SAR data. However, it requires a one-to-one correspondence on pixel-level between the single-look complex (SLC) data of all the used channels and it does not allow to combine the covariance data with other types of features such as textural features or backscattered intensity. Alberga (Alberga 2004) showed that the approach based on the covariance matrix does provide important information about the scatterers on the ground, but that extra information (e.g. backscatter amplitude or texture) can be needed in order to distinguish complex classes.
This led us to the idea to develop an approach that allows to take into account a set of input features with diverse statistical properties, representing for instance radiometric, polarimetric and interferometric information. The developed approach combines feature selection with the combination of the features into a classification function. The approach (Borghys et al. 2004) is 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 us to add features easily. For each class, the logistic regression results in a "detection image". These can be combined to obtain a classification image. Moreover, the logistic regression implicitly performs a feature selection.
In this paper we create a large feature set, consisting of the results of various polarimetric decomposition methods, interferometric and polarimetric coherences, speckle reduced and original SAR data, etc. The main aim of the paper is to investigate the usefulness of each of these features for the detection of the different classes of interest. The paper is only concerned by the influence of the different features on the detection results for each class. For a discussion on the obtained classification results or on the methods to combine the detection results into a classification, we refer to other publications and in particular to (Borghys et al. 2006).

2 THE DATASET

2.1 *SAR data*

The method was applied to a project on humanitarian demining (the *SMART* project, EC IST-2000-25044) for which SAR data at 4 different frequencies were acquired. P-band and L-band are full-polarimetric, dual-pass interferometric. For C- and X-band only VV-polarisation was acquired. All data were delivered as Single-Look Complex (SLC) data as well as geocoded amplitude data. 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.

2.2 *Ground Truth*

A field survey mission was organized 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 (regions) from the test-site. The learning set is used for the optimization of the parameters of the supervised classification. Table 2 shows the twelve classes used for the learning set for this test-site.

Table 1: Classes of interest

1	Abandoned	2	Pastures	3	Barley	4	Wheat	5	Corn	6	Residential
7	Roads	8	FieldsNV	9	Forests	10	Water	11	Hedges	12	Shadows

The agricultural fields were subdivided into C8: "Fields without vegetation" and the three types of crops that visible at the time of image acquistion (barley, wheat and corn). The class C1: "abandoned" refers to formerly cultivated land that has been abandoned. The class C7 can consist of single farms and was indicated as a region encircling the buildings. This means it can contain buildings, parking lots, roads and paths between the buildings, open spaces and trees.

3 THE DERIVED FEATURE SET

From the available SAR data, 80 features were derived. All parameters, except the line detector results, were determined on the SLC slant-range data and results geocoded. For features determined using a sliding window, a 5x5 window was used.

3.1 *Radiometric Information*

The considered radiometric information consists in the original amplitude data for each channel as well as the values in the speckle reduced (Pizurica et al. 2001) log-intensity images.

3.2 *Polarimetric Information*

Different polarimetric decomposition methods were applied to the P- and L-band data. Decomposition methods provide information about the type of scattering produced by the elements on the ground on the radar waves. For the method of Cloude & Pottier (Cloude & Pottier 1997), the CP method, we determined the parameters: entropy H, scattering angle α, combinations of the entropy and anisotropy A: HA, H(1-A), (1-H)A and (1-H)(1-A) and λ1). The other decomposition methods convert the polarimetric information into an abundance value for three types of scattering. For applying these decomposition methods we used the freely available software POLSARPRO. In this article we considered the methods described in (Holm & Barnes 1988), (Huynen 1970), (Freeman & Durden 1998) and (Krogager 1993).

3.3 *Interferometric and polarimetric coherence information*

Besides the parameters of the decomposition methods we also considered the polarimetric coherence. Analogously, from the pairs of dual-pass interferometric images, the interferometric coherences are calculated as well as the combined polarimetric/interferometric coherences.

3.4 *Spatial Information*

Some basic spatial information is included in the feature set. It consists of the results of a bright and a dark line detector (Borghys et al. 2003). The 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 one for the bright lines.

4 DETECTION AND CLASSIFICATION USING LOGISTIC REGRESSION

Logistic regression (LR) (Hosmer & Lemeshow 2000) 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. The logistic regression was carried out using Wald's forward step-wise method. In this method, at each step, the most discriminating 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 also performs a feature selection. The result of applying the logistic regression for a given class in a pixel is the conditional probability that the pixel belongs to the class of interest, given all input features. For finding the parameters of the logistic regression the commercial statistics package SPSS was used.

5 RESULTS AND DISCUSSION

The logistic regression was applied to find the best combination of several subsets of features. In order to compare the adequateness of each combination of features, each time the overall detection accuracy was determined for the different classes. The subsets that were considered are:

- the full feature set
- all features leaving out resp. speckle reduced, amplitude and interferometric data
- only the features derived from resp. the L-band and P-band
- for each decomposition method results were derived when the method is not used and when it is combined with the CP method.

Table 2 presents the detection accuracy obtained by the logistic regression on the learning set. Results are shown for the different classes, for each of the defined subsets of features. In general not using the speckle-reduced data degrades the detection performance. While the speckle reduction adds important information for the classifier, the original amplitude data are not useful.

The interferometric information only affects the results for the classes residential and wheat. Having only P- or L-band data degrades the results for almost all classes. For abandoned land, wheat, corn and residential areas the P-band information is most important. For pastures, barley, roads, fields without vegetation, forests and hedges, the L-band information is most important.

It is very hard to derive a conclusion about the influence of the different polarimetric decomposition methods. It seems that all methods are equivalent for most of the classes.

Table 3 presents an overview of the features that are selected by the logistic regression when the full set of features is given as input. The table gives results for each separate feature and for each class for the radiometric and spatial features. Similar tables were determined for the other parameters (coherences and parameters of the various polarimetric decompositions). These are not shown due to space limitations. The bottom row of the table counts the number classes for which each feature is selected. The second columns counts the number of features that were selected by the logistic regression for distinguishing each class from the others. Apparently most of the features were selected for at least one of the classes. The total number of selected features (including those that are not shown in the presented table) varies from 10 (for water and pastures) to 24 (for barley). The speckle-reduced data seem to be quite important as they are selected for all classes except forests and water. Although one could think the original amplitude data are redundant with the speckle-reduced data, for all classes combinations of both were selected.

The line detector results were selected for each class except water. Although, from the analysis above, the coherence parameters do not seem to influence the overall detection accuracy, they do seem to be selected for the different classes. The interferometric coherence parameters are the most selected; the polarimetric coherence is only very rarely selected. Most of the polarimetric decomposition parameters were selected for at least one class. It seems that more of these parameters are used in L-band. Lband parameters were selected 53 times while the P-band parameters only appear 32 times. This can be explained by the fact that the backscattering mechanisms for the different classes are most discriminative at the shorter wavelength of the L-band (23 cm). For the Cloude decomposition only (1-H)A for P-band was never used. The Holm decomposition is the least selected. The surface scattering of Krogager was never selected and the “odd scattering” of Freeman is only selected 3 times. These results require a further analysis. In particular it could be interesting to investigate the order in which the feature are selected in the iterative LR process and how the feature selection changes when different sub-sets are given as input to the LR or to investigate the discrimination of the classes two-by-two.

Table 2: Detection results (overall detection accuracy in %) for the different classes and for the various defined sub-sets of features

Class Nr:	1	2	3	4	5	6	7	8	9	10	11	12
Full Set	86.6	84.1	98.2	95.2	86	91.7	94.2	91.6	99.8	99.1	93.8	98.1
No Speckle Red	85.7	84.5	95.4	93.9	84	89.2	91.2	90.7	99.5	99.2	88.7	96.8
No Amplitude	87	84.8	98.2	96.7	86	91.5	94.6	91.5	99.5	99.4	94.5	98.2
No Interferometry	87.2	84.3	99.2	94.9	86	90	94.8	91.3	99.7	99.3	93.7	98.4
Only Lband	80.6	83.6	97.8	85.5	77	80.1	90.5	90.8	99.5	99	90.8	94.2
Only Pband	84.1	79.9	88.5	90.6	79	88.3	82.4	84.1	95.9	98.3	89.5	89.7
Only CP	86.1	85.3	98.7	95.7	85	90.7	94.8	89.8	99.5	99.4	93.8	97.3
No CP	87.4	84.4	98.1	95.5	86	89.4	94.1	90.6	99.5	99.4	93.6	97.7
No Barnes	87.4	85.3	98.8	95.4	86	91.3	94.4	92.2	99.9	99.5	94.4	98.4
No Freeman	87.6	85.7	98.9	95.3	87	92	94.3	92.7	99.9	99.2	93.9	97.4
No Holms	87.6	85.9	99.2	96.3	88	92	94.9	91.6	99.4	99.3	94.5	98.7
No Huynen	87.6	86	98.8	95.4	87	91.8	94.9	91.6	99.4	99.2	94.5	98.6
No Krogager	87.8	85	98.5	96.7	87	91.6	94.2	92.3	99.4	99.3	94.5	98.1
CP+Barnes	87.7	84.9	97.4	95.8	87	91.5	94.2	90.7	99.6	99.4	93.9	97
CP+Freeman	86.6	84.3	98.8	95.6	86	90.8	95	90.2	99.4	99.5	94.7	97.2
CP+Holms	86.7	85	98.7	95.6	86	90.8	94.7	91.5	99.5	99.4	94.4	97.5
CP+Huynen	86.4	85.3	98.3	95.8	86	92	94.6	91.6	99.5	99.4	94.3	97.4
CP+Krogager	86.5	85	98.7	95.8	86	90.7	95.4	92.1	99.5	99.6	94.3	97.8

Table 3: Overview of selected parameters for the radiometric and spatial features

		Speckle Reduction								Original Amplitude							LD		
	Nr of Feat	Lhh	Lhv	Lvv	Phh	Phv	Pvv	Cvv	Xvv	XVVAMP	LHHAMP	LXXAMP	LVVAMP	PHHAMP	PXXAMP	PVVAMP	Bright Line De	Dark Line Det.	TotalNr of Feat
Abandoned	9	1				1	1	1	1		1			1	1			1	17
Pastures	3		1					1										1	10
Barley	8	1		1		1		1	1				1			1	1		24
Wheat	10			1	1	1		1		1			1		1	1	1	1	20
Corn	8		1	1	1		1					1	1				1	1	17
Resi	7		1	1	1							1		1		1		1	21
Roads	9		1	1	1			1	1					1	1	1		1	17
FieldsNV	5	1				1					1				1		1		14
Forests	3											1	1				1		11
Water	5									1	1		1	1		1			10
Hedges	4		1				1									1	1		13
Shadows	5	1							1		1			1				1	16
# Selec.		4	5	5	4	4	3	5	4	2	4	3	5	5	4	6	6	7	

6 CONCLUSION

A method for feature-based supervised classification, using logistic regression (LR), is presented. The method is applied on a set of multi-channel SAR data. Twelve classes were defined. The method is applied to discriminate each class from all others. A large feature set was determined. The main topic of the paper was to investigate the influence of these features on the overall detection accuracy and to use the feature selection property of the logistic regression to investigate the selection of parameters for the different classes. Most parameters seem relevant for at least one class. For the different polarimetric decomposition methods some seem much more effective than others. The interferometric coherence is more important than the polarimetric or the combined polarimetric/interferometric coherence. It is important to add spatial information to the feature set. This was done here by means of the results of line detectors. Other types of spatial operators (e.g. texture parameters) should be examined. The obtained results need to be analysed further. In particular it could be interesting to investigate how the feature selection changes when different sub-sets are given as input to the LR or to investigate the discrimination of the classes two-by-two.

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