Land-cover classification using fused PolSAR and PolInSAR features

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Abstract

Due to the low information content of individual SAR images, single-band SAR data do not provide highly accurate land cover classification. However, in areas under risk where rapid land cover mapping is required, the advantages of SAR which include cloud penetration and day/night acquisition, are evident in comparison to optical data. The main research goal of this study is to fuse different frequency Polarimetric SAR (PolSAR) data as well as Polarimetric Interferometric (PolInSAR) data for land cover classification. Fusion techniques at two different levels are applied and combined in this study: the Logistic Regression (LR) as 'feature based fusion' method and the Neural-Network (NN) method for higher level fusion. Based on the results presented in this research we found that fused features from different SAR frequencies are complementary and adequate for land cover classification. Moreover, it has been found that PolInSAR features are complementary to the PolSAR information and essential for producing accurate land cover classification.

1 Introduction

If single band monopolarisation SAR systems are used, there is generally a considerable degree of ambiguity between different types of land cover. To overcome this, the dimensionality of the observation needs to be increased [1].

The fusion of multisensor data containing SAR data, has received large attention in the remote sensing literature [2]-[4] and mainly fusion of SAR with optical data [5]-[12]. However, in case of area under risk (e.g. flood, earthquake, land mines) where risk assessment and rapid land cover mapping is required, the advantages of SAR which include cloud penetration and day/night acquisition are evident in comparison to the optical data.

Thus, it seems that there is strong need to combine modern SAR techniques and sensor technologies and to study their advantage capabilities for land cover applications. In Polarimetric SAR (PolSAR), the tight relation between the physical properties of natural media and their polarimetric features, leads to highly descriptive results that can be interpreted by analysing underlying scattering mechanisms. Interferometric SAR data on the other hand provides information concerning the coherence of the scattering mechanisms and can be used to retrieve information about the structure and the complexity of the observed objects. When utilised concurrently, these different capabilities potentially allow substantial improvements in land cover determination [13]-[14].

Polarimetric Interferometric SAR (PolInSAR) imaging that recovers textural and spatial properties simultaneously has proved to be a valuable tool for several remote-sensing applications through the estimation of vegetation height, tomography, and the classification of crops and forest [15]-[17]. However, PolInSAR is a relatively new image processing technique, and the physics behind, is still in exploration. Due to the complexity of the mathematics and of the image processing behind, it is under critics and its added value (mainly to the PolSAR information) is still uncertain.

The main research goal of this study is to fuse different frequency PolSAR and PolInSAR data for land cover classification in mine covered areas. Due to the high risk for human life and the necessity for quick, good and very accurate mapping; the exploration and the extraction of maximum information from the SAR scene is explored in this paper. In the imaging process several PolSAR and PolInSAR features were extracted, each combining phase, amplitude and correlation information in order to highlight specific characteristics of the scene. For land cover feature recognitions and land cover classification, two levels of fusion were applied. In the feature-level fusion, logistic regression (LR) is used for feature selection and for combining/fusing the selected features by optimizing a well-defined log-likelihood function for each of the classes. The obtained probability images are then fused using Neural-Network (NN) soft decision fusion in order to obtain the final classification results.

2 Data set

The data used for this research consists of SAR and ground truth data that have been collected under the frame of EC-FP6 project 'SMART' [18], in post-war land mines affected zone 'Glinska Poljana' in the Centre of Croatia. This site is a 12 kilometres square semi-urban area containing the following land-cover features: residences, roads, forests, different crop fields, pastures, abandoned areas (due to the mines cover areas), bare soil and rivers. The SAR data that were used for this research were obtained in the 8 of August 2001 using separate E-SAR airborne full-polarimetric L-band, P-band and dual pass interferometry data.

3 Features extraction

For exposing different properties of the land cover objects and for the fusion processes a total of 76 different PolSAR and PolInSAR features were extracted. The P-band SAR features were registered to the L-band SAR data using a second-degree polynomial transformation and with sub-pixel precision. The features were extracted using the 'PolInSAR' tool developed in CSL (Central Spatial de Liege©), the PolSARPro program (ESA©) and by automatic tools developed at the SIC (Signal and Image Centre).

Using full-polarimetric E-SAR L-band and P-band SLC data, 50 PolSAR features were extracted by applying 7 PolSAR decomposition techniques: Pauli [19], Freeman [20], Krogager [21], Holm [22], Huynen [23], Barnes [22] and Cloude (also known as $H/A/\alpha$ and asymetry) [24] and by calculating the PolSAR coherences [25].

Using the PolInSAR L-band and P-band a set of complex coherences [26], [27] was constructed as described by [28], for each pixel in the original data. These coherences can be geometrically represented in complex unitary circle (CUC).

For each pixel they form a cloud in the CUC that can be approximated by an ellipse, which is characterised by the following parameters [26]:

- the shape parameters of the ellipse λ_1, λ_2 that are the measures of the lengths of the long and the short axis of the ellipse respectively;
- the mean magnitude and mean phase of the complex coherence set, which describe the position of the centre of gravity of the ellipse;
- the standard deviation of the magnitude and of the phase.

The Neumann decomposition [26] combines the shape elements into three parameters: *pseudo-ellipticity, coherence/phase SDEV relationship and the outward tendency*. Using the 'optimal coherences' [29] we produced the two classifiers [30] A_1 and A_2.

In total, 26 different PolInSAR features were constructed for the following fusion process.

4 Fusion methodologies

The feature extraction processes result in a large feature set: 25 L-band PolSAR features, 25 P-band PolSAR features, 13 L-band PolInSAR features and 13 P-band PolInSAR features.

Based on the ground truth study we identified nine different land cover classes: residence, road, forest, wheat crop field, corn crop field, bare soil, abandoned area (with no tree or shrubs) and river.

In this research, for land cover feature recognitions and land cover classification, two levels of fusion were applied. In the feature-level fusion the different features extracted from the PolSAR and the PolInSAR data were combined using logistic regression in order to create probability images for each land cover class and for each set of input data (L-band PolSAR, PolInSAR and P-band PolSAR and PolInSAR). The obtained probability images are then fused using Neural-Network (NN) soft-decision fusion in order to obtain the final classification results.

4.1 Feature-level fusion using logistic regression

Logistic regression (LR) [31] is developed for dichotomous problems where a target class has to be distinguished from the background. LR estimates the conditional probability of an event (current pixel belonging to the target class) occurring using the independent variables (the extracted features in our case). The odds of this probability in pixel (x,y) is modelled by: (1)

$$\frac{p_{x,y}\left(tgt\middle|\vec{F}(x,y)\right)}{1-p_{x,y}\left(tgt\middle|\vec{F}(x,y)\right)}=\exp\left(\beta_0+\sum_{i=1}^{k}\beta_i F_i(x,y)\right)$$

with $\vec{F}(x,y)$ the vector of available features in pixel x,y, and $F_i(x,y)$ the value of the i^{th} feature at x,y.

In order to identify a subset of features that are good predictors of the dependent variable, stepwise selection of the features is used. The iterations stop when adding a new feature to the model does not improve $L_{x,y}(\beta)$ significantly. The step-wise LR performs a feature reduction by adding one by one feature into the model in order of decreasing discriminative power.

4.2 High level fusion using a neural network

A multi layer perceptron NN with one hidden layer and nine output nodes (one for each class) was used for fusing the probability images provided by the logistic regression. The relation between the input and the output node is given by the following formula [32], [33]:

$$y_k = f\left(\sum_j w_{kj} f\left(\sum_i w_{ji} x_i + w_{j0}\right) + w_{k0}\right), \quad (2)$$

where the inner sum is a weighted linear combination of the inputs, f is a non-linear function and the outer sum is a weighted linear combination of the outputs of the hidden layer nodes. The weights represent the connection strength between the nodes of two consecutive layers. The network was trained using the back-propagating errors algorithm [34]-[35].

Fig. 1 presents a scheme of the complete fusion processes applied in this research.

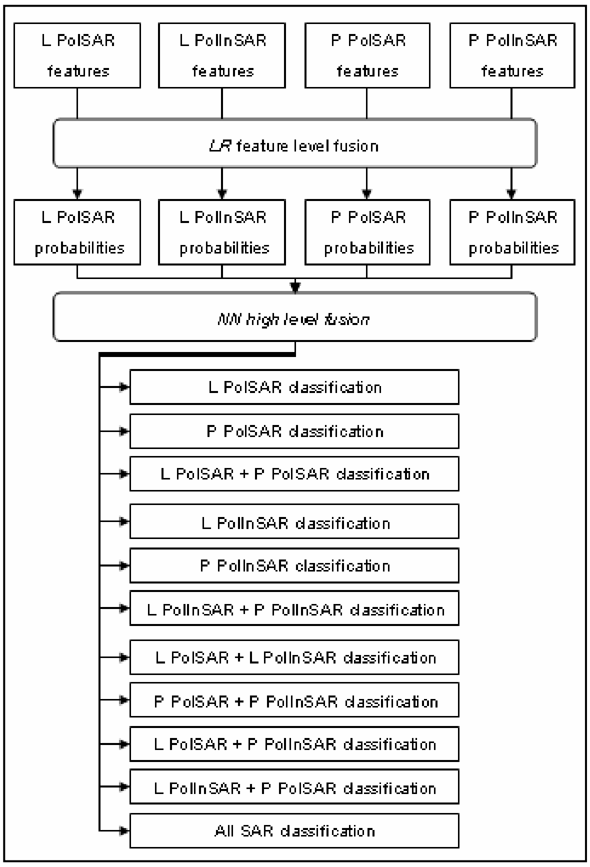

Fig. 1. The fusion process scheme

5 Results

The final results are eleven NN fusion based classifications. Two training data sets and one verification set were obtained using the ground truth campaign. Producer's accuracy (PA) and User's Accuracy (UA) for the NN fusion processes were derived using the verification data set.

For seven of the nine land cover classes (Table 1), the best results were derived using the 'All SAR' probability data sets. For all the classes, the highest PA and UA results were obtained using fused PolSAR and PolInSAR data sets. These results emphasises the complementary of the different SAR frequency data sets and the PolSAR and PolInSAR information for land cover classifications. The highest PA (99.51%) and UA (99.35%) results were obtained for the abandoned-area class.

TABLE 1
THE HIGHEST PA AND UA RESULTS PER CLASS OBTAINED USING NN CLASSIFIER

Land cover class	*NN classification*		
	The best fusion set	PA %	UA %
Residences	All SAR	90.31	68.81
Roads	All SAR	41.84	62.67
River	All SAR	61.64	81.73
Forest	All SAR	91.60	88.08
Bare soil	All SAR	89.32	79.92
Abandoned areas	All SAR	99.51	99.35
Wheat	All SAR	99.03	97.53
Corn	L PolSAR + L PolInSAR	65.31	66.27
Pastures	L PolInSAR + P PolSAR	31.35	29.58

Table 2 presents the overall accuracies and the Kappa for the land-cover classifications made using the NN classifier. The results in Table 2 show that for the complete land cover classification, the classification accuracy improves by using fused data sets from different SAR frequencies. The highest accuracy is obtained using the All-SAR data set (84.00%) and kappa of 0.809. The results highlight again the complementary in using PolSAR and PolInSAR information.

TABLE 2
OVERALL ACCURACY FOR LAND COVER CLASSIFICATION OBTAINED USING THE NN CLASSIFIER

LR probability data set	NN	
	Overall accuracy	Kappa
L PolSAR	52.13	0.437
P PolSAR	59.72	0.522
L+P PolSAR	67.48	0.618
L PolInSAR	61.04	0.539
P PolInSAR	37.69	0.522
L+P PolInSAR	66.16	0.601
L PolSAR + L PolInSAR	63.87	0.576
P PolSAR + P PolInSAR	65.55	0.596
L PolSAR + P PolInSAR	63.22	0.569
L PolInSAR + P PolSAR	69.96	0.646
All SAR	84.00	0.809

6 Conclusions

Based on the results presented in this article we can state that fused features from different SAR frequencies are complementary and adequate for land cover classification. It was also found that PolInSAR features are complementary to the PolSAR information and essential for producing accurate different land cover classification. E-SAR full polarization and interferometry data proved to produce valuable remote sensing information and can be used to obtain accurate information for areas under danger or stress. The two fusion techniques applied in this study and the image processing chain selected for this research were found to be valuable tools for data reduction, feature selection and fusion based classification.

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