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### Review

# Fusion of PolSAR and PolInSAR data for land cover classification

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#### ABSTRACT

The main research goal of this study is to investigate the complementarity and fusion of different frequencies (L- and P-band), polarimetric SAR (PolSAR) and polarimetric interferometric (PolInSAR) data for land cover classification. A large feature set was derived from each of these four modalities and a two-level fusion method was developed: Logistic regression (LR) as 'feature-level fusion' and the neural-network (NN) method for higher level fusion. For comparison, a support vector machine (SVM) was also applied. NN and SVM were applied on various combinations of the feature sets.

The results show that for both NN and SVM, the overall accuracy for each of the fused sets is better than the accuracy for the separate feature sets. Moreover, that fused features from different SAR frequencies are complementary and adequate for land cover classification and that PolInSAR is complementary to PolSAR information and that both are essential for producing accurate land cover classification.

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#### 1. Introduction

Classification of land cover is one of the primary objectives in the analysis of remotely sensed data. Due to the low information content of individual SAR images, single-band SAR data do not provide highly accurate land cover classification (Herold et al., 2004; Torma et al., 2004). However, in areas under risk where rapid

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land cover mapping is required, the advantages of SAR, which include cloud penetration and day/night acquisition, are evident in comparison to optical data.

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 number of degree of freedom of the observation needs to be increased (Corr et al., 2003). Combining multi-frequency SAR scenes has proved to be a valuable tool for distinguishing different land features (Benz, 1999; Solaiman et al., 1999; Pellizzeri et al., 2002; Min-Sil and Moon, 2003; Zheng et al., 2006). Fusion of multi-aspect and multitemporal SAR data was successfully applied for road detection in dense urban areas (Tupin et al., 2002) and for change detection (Onana et al., 2003), respectively. In PolSAR, the tight relation between the physical properties of natural media and their polarimetric behaviour leads to highly descriptive results that can be interpreted by analyzing underlying scattering mechanisms. Fusion of physical and textural information that are derived from various SAR polarizations has enhanced the classification results (Crawford et al., 1999; Borghys et al., 2007). Interferometric SAR data provide information about the structure and the complexity of the observed objects. When utilised concurrently, these different capabilities allow substantial improvements in land cover determination (Gamba and Houshmand, 1999; Hong et al., 2002). Lately, high-level decision fusion was applied to improve the monitoring of alpine glaciers using qualitative geophysical parameters, PolSAR and interferometric SAR (Vasile et al., 2007).

Multisensor fusion, combining SAR and optical data, received large attention in the remote-sensing literature (Solberg et al., 1994; Kierein-Young, 1997; Farina et al., 2001; Alparone et al., 2004; Torma et al., 2004; Shimoni et al., 2007). The challenging task of fusing hyperspectral and SAR imagery was recently investigated with promising results (Chen et al., 2003; Borghys et al., 2007).

Fusion of SAR data for land cover application was performed in three different levels; pixel, feature, and decision, and the adopted approaches include statistical methods (Farina et al., 2001; Hong et al., 2002; Pellizzeri et al., 2002; Chen et al., 2003; Alparone et al., 2004; Zheng et al., 2006) Bayesian methods (Crawford et al., 1999), Dempster–Shafer (DS) evidence theory (Min-Sil and Moon, 2003), fuzzy-logic (Benz, 1999; Solaiman et al., 1999; Tupin et al., 2002; Shimoni et al., 2007; Vasile et al., 2007), neural networks (Xiao et al., 1998; Melgani et al., 2003; Solberg and Jain, 1997) Markov random fields (Solberg et al., 1996) and support vector machines (Fukuda and Hirosawa, 2001; Lardeux et al., 2006, 2008; Jiang et al., 2007).

The 'Wishart distance classifier' (Lee et al., 2001) has often been used for unsupervised/supervised classification (Corr et al., 2003) of PoISAR data. This method uses the amplitudes of the elements in the covariance or coherency matrices. However, it does not take explicitly into consideration the phase information within polarimetric data, which plays a direct role in the characterization of a broad range of scattering processes (e.g. in single and doublebounce scattering (Van Zyl, 1989; Freeman and Durden, 1998). Furthermore, the covariance or coherency matrices are determined after spatial averaging and therefore can describe only stochastic scattering processes while certain objects, such as man-made objects, are better characterized at pixel-level (Cameron et al., 1996).

Polarimetric interferometric SAR (PolInSAR) imaging that recovers textural and spatial properties simultaneously has proven to be a valuable tool for several remote-sensing applications through the estimation of vegetation height, tomography, and the classification of crops and forest (Reigber et al., 2005; Garestier et al., 2006; Fornaro and Serafino, 2006). However, PolInSAR is a relatively new image processing technique, and at the present the physics behind is clear for forest, but it is still in exploration for other land cover types. In the last few years several polarimetric decomposition representations have been developed for specific applications; each of them combines the polarimetric or PolInSAR information in order to characterize a certain type of scattering process. The best features for a given application are either determined through experience, physical grounds (e.g. Hoekman and Quirones, 2000) or by systematic selection and reduction process (e.g. Cumming and Van Zyl, 1989). In very complex scenes it is useful to exploit the discriminative power offered by the combination of a great number of these features. However, because of their diverse statistical properties, standard feature selection procedures cannot be applied.

The data used for this research consist of SAR and ground truth data that have been collected in the frame of the 'SMART' project (RMA, 2006), which was funded by the European Commission – Sixth Framework Program. The research area is a 12 km<sup>2</sup> semiurban area located in 'Glinska Poljana' in the centre of Croatia that is a post-war land mines affected zone. Due to the frequent cloud covers and the necessity for up-to-date land cover mapping, the 'mine action unit' in Croatia as end-user, found SAR images to be the most valuable remote-sensing source. The land cover mapping serves for 'suspected area' reduction and not for mine detection. Those suspected areas are abandoned areas where human activity has ceased, and the risk for the presence of mines is high.

Lately, different datasets of Glinska Poljana, which were collected during the 'SMART' campaign, were studied under the frame of two fusion researches. Borghys et al. (2006) combined L-and P-bands full polarimetric SAR data and X and C bands with VV polarization for land cover classification using the LR and multinomial logistic regression (MNLR) methods. Bloch et al. (2007) used the Dempster–Shafer (DS) and a method based on fuzzy-logic to fuse the complete SAR dataset described above with Daedalus high resolution, 12 bands multispectral data, which covers the visible, near infra-red and the thermal infra-red wavelengths.

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 are extracted, each combining phase, amplitude and correlation information in order to highlight specific characteristics of the scene. For land cover classification, two levels of fusion are applied. In the feature-level fusion, logistic regression (LR) is used for feature selection and for combining/fusing the selected features by optimizing a welldefined 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. For comparison, the support vector machine (SVM) classifier, which is well suited to handle numerous heterogeneous and non-linearly separable variables (Lardeux et al., 2008), was implemented directly on the SAR features and after applying the Fscore as feature selection criterion. This paper uses both pixel-wise and stochastic parameters and proposes a general method for feature selection and feature combination.

#### 2. Dataset

The SAR data used for this research were obtained in August 2001 and consist of E-SAR (European SAR) airborne full-polarimetric, dual-pass interferometric data in both L- and P-band. The main characteristics of the E-SAR data are presented in Table 1. During and before the flight campaign ground teams were Download English Version:

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