CLASSIFYING MULTILEVEL SEGMENTED TERRASAR-X DATA, USING SUPPORT VECTOR MACHINES

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ABSTRACT

To segment a image with strongly varying object sizes results generally in under-segmentation of small structures or over-segmentation of big ones, which consequences poor classification accuracies. A strategy to produce multiple segmentations of one image and classification with support vector machines (SVM) of this segmentation stack afterwards is shown.

1. PROJECT PURPOSE

Since several years the water management authorities of the European member states are implementing a framework for community action in the field of water policy, which have been passed as EU Water Framework Directive in 2000 [1]. The general aims of this framework are, among others, preventing and minimizing water pollution, supporting sustainable water usage and general environmental protection, and mitigating the effects of floods. At the beginning, member states must identify and analyze individual river basin and district. In this context, for example, the mapping of structure-ecological status of rivers is required. Finally they adopt management plans and programs of measures for each water body.

Usually the structure-ecological mapping of the water body is done by field work. However, field work is time consuming and cost-intensive. Moreover, it depends on the expert knowledge and experience of the field analyst and results of different field campaigns are not necessarily comparable. Behind this fact the joint research project HYDRA, funded by the DLR/BMBF (FKZ 50EE0917), aims on the support of the required field work in context of the Water Framework Directive, using SAR and multispectral remote sensing data (e.g. TerraSAR-X and RapidEye). (Semi-) automated procedures will be developed that can be used for (pre-) mapping in structure-ecological surveys of river courses. Thus, the number of parameters, which have to be adjusted in field work, can be reduced.

2. MAPPING STRATEGY

Potential parameters, which are relevant for the water structure mapping as well as can be derived by remote sensing data, are among others: (i) river course and shore lines, (ii) river banks, (iii) surrounding land use / land cover and (iv) transversal structures. Whereas some parameters can be derived by simple standard image processing methods, others require the design of new image analysis methods or the adaption and extension of existing methods (Fig. 1). The delineation of wide rivers, for example, seems relatively simple and can be performed by object-based image analysis. In this context standard image segmentation techniques, e.g. region growing [2], and an adequate classification method, e.g. support vector machines (SVM) [3], [4], [5], can be used to generate the final result. However, it has been shown in different studies that the size of natural objects can have an impact on the classification accuracy and consequently, the detection of narrow rivers may be challenging. Segmentation algorithms mostly fail in separating very narrow objects and the use of alternative methods seems necessary. Methods based on Markov random fields [6] or mathematical morphology [7] may overcome this problem. Most transversal structures, such as bridges and dams, are linear elements, and can be perhaps detected by similar methods. However, neighborhood information between two separated river segments and a road help to merge the separated river parts and to define the transversal structure as bridge.

The land cover that is surrounding the river is another important input information and several studies have been published in this context [8], [9], [10]. The presented approach is aiming on the multilevel-segmentation of SAR data. The main objectives of the paper are: (i) testing the influence of different segmentation levels on the classification accuracy and (ii) the benefit of multiply segmentation levels for the classification. Minor objectives are the profit of (i) multitemporal features and (ii) the fusion with optical data. The methodology is described explicit below.

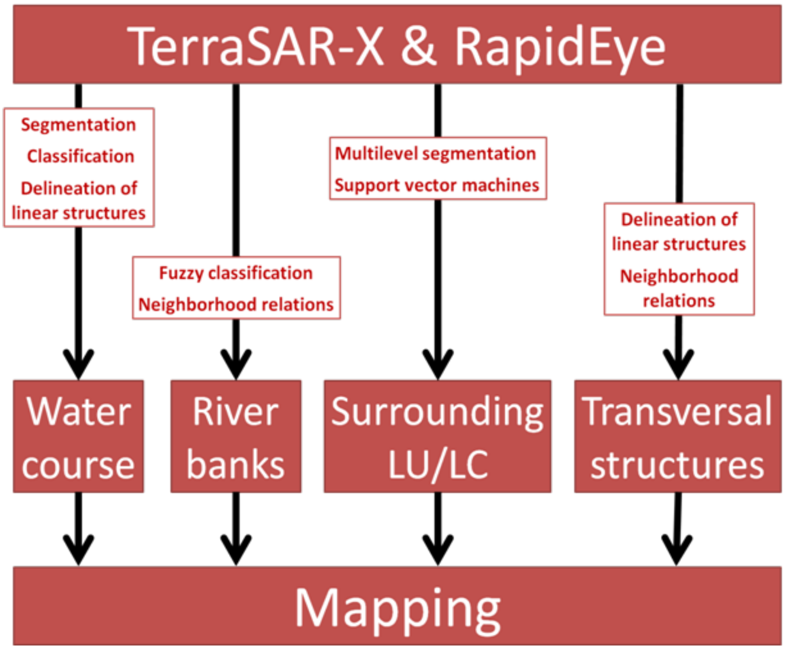

Figure 1: Mapping strategy of the project HYDRA

3. STUDY AREA AND DATA PRE-PROCESSING

The study area is located in the north-west of Freiburg i. Br., Baden-Württemberg, Germany, where the rivers Dreisam, Elz, and Alte Dreisam coalesce into the Leopoldskanal and the Alte Elz. This region provides rivers of several widths and thereby very useful for the study purpose (Fig. 2). For this area several TerraSAR-X (TSX) images are available. For this study three Stripmap dual polarized scenes (HH/HV, 2009/05/03, 2009/07/04 and 2009/08/05) with the same orbit and beam information are chosen. Thus the coherence between two images can be derived [11]. The images are co-registered and geo-coded to a 5 m x 5 m pixel spacing with GAMMA [12]. After that speckle suppression was applied with a Lee-Sigma filter [13] with a window size of 9 x 9.

4. IMAGE ANALYSIS

4.1 Segmentation Method

In many remote sensing land cover classifications the accuracy is increased by integrating spatial information into the classification process. Many of these studies use object based approaches, which perform image segmentation before the image classification [14], [15]. However, it is difficult to generate one single segmentation level for all image objects. Inadequate segmentation can actually decrease the classification accuracy [16]. Beside the strategy to improve the segmentation accuracy [17], [18], there are studies, which use different levels of segmentation for the classification [19], even if it was not tested on high resolution SAR data until now. In this study three levels of segmentation are generated, where the segments of level 1 (L1) are super-objects for the segments of level 2 (L2) and level 2 for level 3 (L3) as well (Fig. 3). L1 is generated to delineate large image objects, while L3 fits small objects. The segmentation is generated with the multiresolution segmentation method in eCognition [2], using an image stack, consisting of all TSX images.

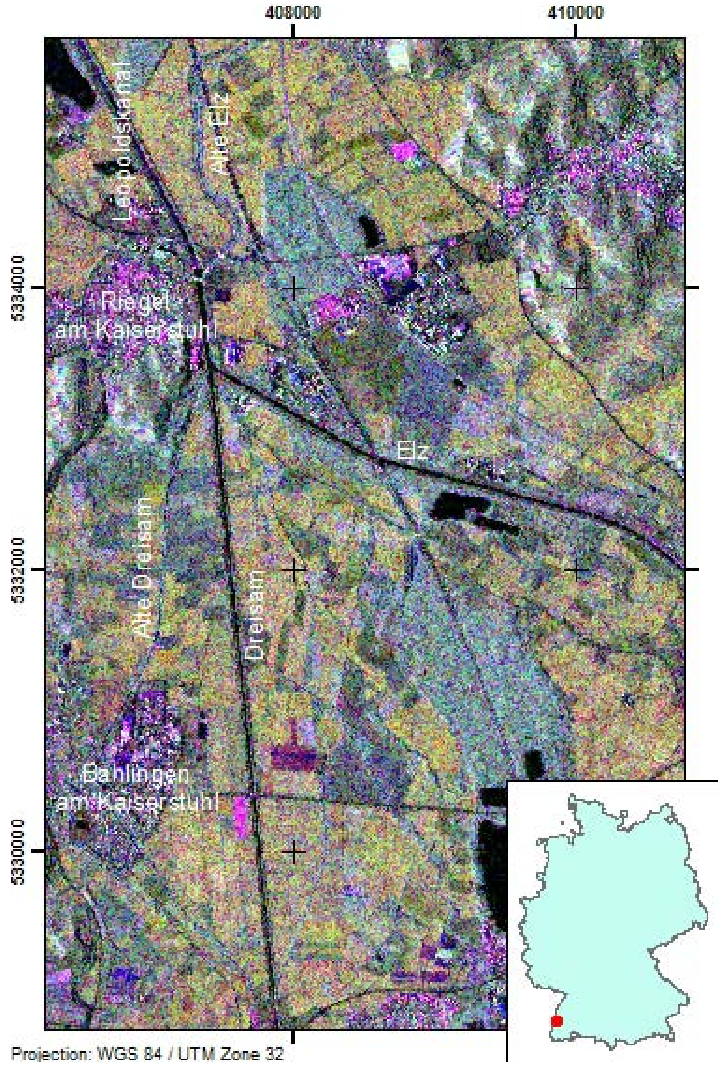

Figure 2: Study area (image composite: R: 2009/03/05 HH, G: 2009/03/05 HV, B: 2009/04/07 HH)

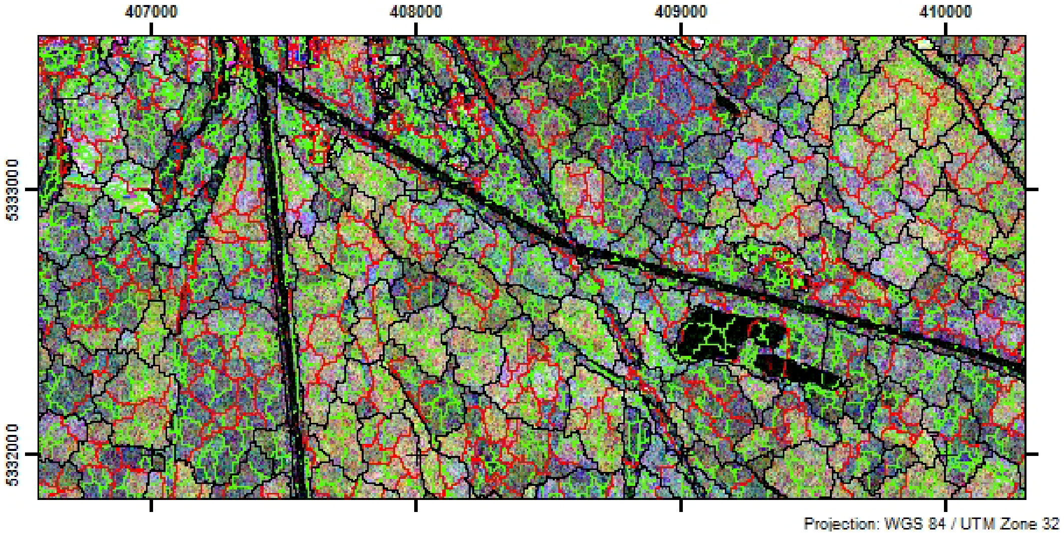

Figure 3: Multilevel segmentation (L1: black, L2: red, L3: green, image composite: R: 2009/03/05 HH, G: 2009/03/05 HV, B: 2009/04/07 HH)

4.2 Classification Method

In several studies it was shown that SVMs outperform conventional classifiers (e.g. maximum likelihood) in terms of accuracy [5], [20], so it is the method of choice in this study, using imageSVM, a freely available IDL/ENVI extension [21]. The classification is aiming on five main land cover classes (grassland, arable, settlement area, forest and water). These classes were chosen, because this information directly supports the mapping of the water structure [10]. The SVM is trained with 200 samples per class. A Gaussian RBF Kernel was used and the parameterization was done automatically by a grid search, testing different Kernel function parameters and regularization parameters [22]. Initially the six intensity images were classified at each segmentation level and at pixel level. The second classification based on the intensity images of all segmentation level (18 information layers).

5. EXPERIMENTAL RESULTS

The results clearly underline that the segmentation significantly improves the classification of SAR data. The result of the classification at pixel level is very noisy (Fig. 4) and the overall accuracy is far below the results at any tested segmentation level (Fig. 5). The classification results that are based on L1 and L2 do not show significant differences (~69-69.4%), while the accuracy is slightly decreased by the smallest level L3 (67.4%). The visual comparison confirms that the noise is significantly reduced by image segmentation. Level 2 performs best in the visual comparison of the three levels; anyhow large structures are better detected in L1 and small ones in L3. Consequently, the classification of all three levels seems adequate, as confirmed by the accuracy assessment. The combination of all levels outperfomed all single levels in terms of the overall accuracy and most class accuracies. (Fig. 5, Tab. 1). The visual assessment demonstrates good separation of larger objects (e.g. the grassland in the northern part of the study area) as well as of regions that are characterized by a relatively small objects and spatially high frequent changes of land cover, such as the grassland and arable field plots in the western part of the study site.

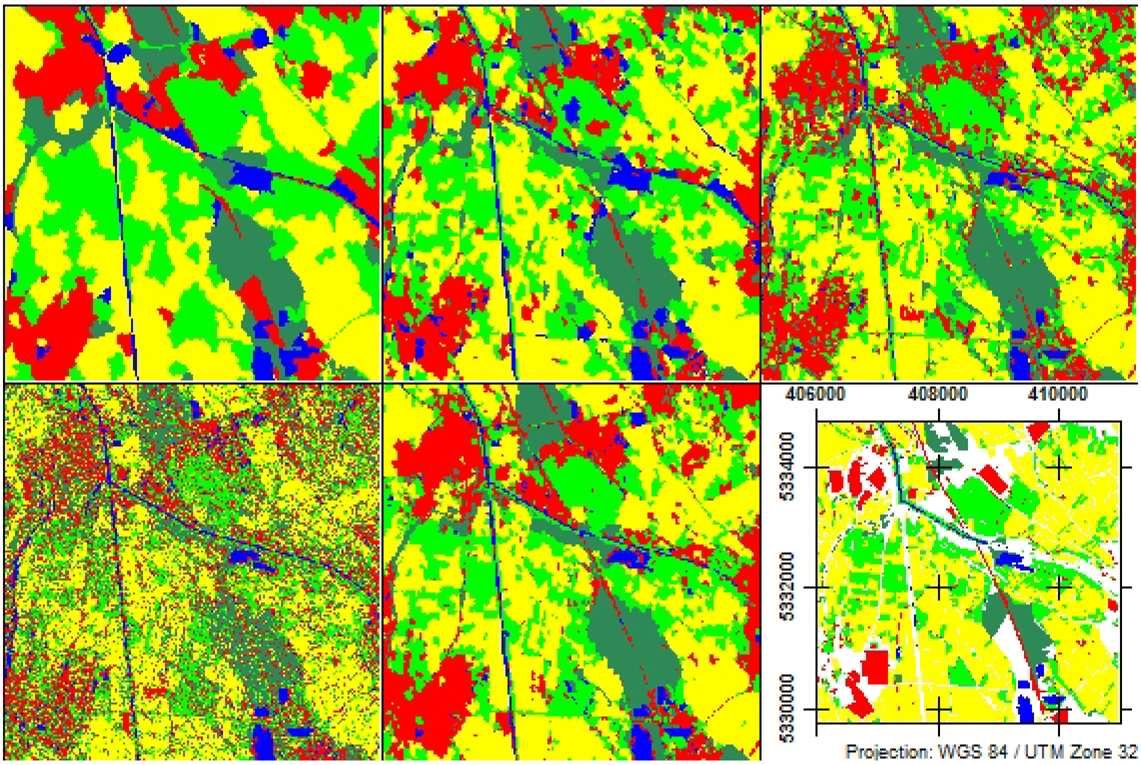

Figure 4: Classification results (upper left: L1, upper middle: L2, upper right: L3, lower left: pixel level, lower middle: all levels, lower right: ground truth; green: grassland, yellow: arable crop, red: built-up area, dark green: forest, blue: water)

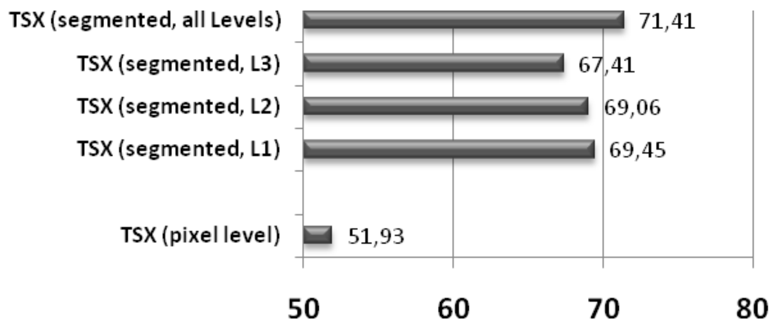

Figure 5: Overall accuracies [%] using different levels of segmentation

Table 1: Producer and user accuracies [%], using different levels of segmentation

	Segmentation L1		Segmentation L2		Segmentation L3	
	Producer	**User**	**Producer**	**User**	**Producer**	**User**
Grassland	64.28	47.73	62.37	46.57	59	47.23
Arable	68.93	90.44	69.24	90.67	68.54	91.89
Built-Up	73.81	42.98	73.25	41.44	70.37	30.3
Forest	88.1	54.3	84.99	54.57	82.14	46.07
Water	88.12	50.83	86.44	49.26	77.09	78.14
	Pixel level		**all Segmentlevels**		**all Segmentlevels + features**	
	Producer	**User**	**Producer**	**User**	**Producer**	**User**
Grassland	38.34	40.06	64.88	51.2	63.3	47.92
Arable	55.54	86.9	71.69	92.08	73.57	91.92
Built-Up	46.92	16.3	79.63	36.46	81.45	55.31
Forest	58.85	15.52	82.98	62.37	86.46	53.22
Water	77.51	54.28	80.45	68.75	89.55	61.59

6. CONCLUSIONS AND OUTLOOK

The results clearly demonstrate the positive impact of image segmentation on the classification accuracy. Moreover, using the information of more than just one segmentation level improves the result of the classification. However, the definition of an adequate classification strategy is an ongoing process. The approach can be easily extended, for example, by including multitemporal features and multispectral images in the classification process. It has been shown that multitemporal information increases the classification accuracies [23]. Beside the intensities of the TSX data following information layers (each in HH and HV) are derived and incorporated into the classification: the mean coherence of the two coherence images between date 1 and date 2 and between date 2 and 3, the standard deviation, the temporal standard deviation of db Values [23] and the temporal mean. In addition the spatial standard deviation of the intensities, temporal mean intensities and coherences in each segment are computed. The use of the whole data set (22 features) significantly improves the classification (Tab. 1). Moreover, the use of multispectral data can improve the classification result. [19], [24]. In this study, a single RapidEye image (2009/05/30) was included, increasing the classification accuracy up to 77%.

7. ACKNOWLEDGMENTS

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