CLASSIFYING SEGMENTED MULTITEMPORAL SAR DATA FROM AGRICULTURAL AREAS USING SUPPORT VECTOR MACHINES

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ABSTRACT

In the presented study the performance of support vector machines (SVM) for classifying segmented multi-temporal SAR data is investigated. Results show that multi-temporal SAR data from an area dominated by agriculture can be successfully classified using SVM. Classification accuracy (78.2%) and degree of differentiation between land cover types is similar or better than results achieved with a decision tree classifier. A positive influence of image segmentation on classification results can be reported which varies with object size. A comparison of classification results derived on different aggregation levels shows, that a medium segment size should be preferred. It is better to work with segments that are smaller than the natural features of interest and segments that are greater than natural features should be avoided.

INTRODUCTION

Land cover classifications are one of the widest used applications in the field of remote sensing. Supervised classification techniques are often used in this context. Besides the chosen classification algorithm, the set of training samples as well as the input images or input features are dominating factors for the accuracy and performance of a supervised classifier (i,ii). The availability of both ground truth data and remote sensing imagery are often limited and can not be influenced by the user. In addition neither the training samples nor the selected features can be assumed to be *ideal* for a representative training. Against this background, the choice of an adequate classification approach is an important step in data analysis.

Regions with agricultural land use are investigated in many remote sensing based land cover studies. Mono-temporal approaches can be inefficient due to great temporal variability of individual plots. In several studies the classification accuracy is increased by multi-temporal data sets (iii,iv). Thus multi-temporal applications seem more appropriate for land cover classifications. However, the availability of optical data is often limited by solar illumination and cloud cover. This is a drawback, particularly for operational monitoring systems. Hence SAR data, which are independent from these factors, are better suited for multi-temporal applications. In regard to upcoming missions with high revisit times and better spatial resolutions like TerraSAR-X, multi-temporal approaches become even more interesting. Considering such future datasets with high spatial and temporal resolution adequate classifiers are needed.

Statistical methods like the maximum likelihood classification are widely known. They can achieve good results, if an adequate data distribution model is known (v). In the context of many remote sensing applications a Gaussian distribution of the data is assumed; admittedly such an assumption is not necessarily met and the approach might in many cases be inefficient. Hence non-parametric approaches, like self-learning decision trees (DT) or support vector machines (SVM) have been introduced (ii,vi,vii,viii). The concept of SVMs is well known in pattern recognition and has lead to good results in several remote sensing studies for the classification of optical data (vii,viii). In contrast to other non-parametric methods only a few studies are known that use the approach for classifying SAR data (ix,x). In several studies segment based classifications outperform per-pixel approaches (xi,xii). This seems particularly interesting in regard to the SAR typical noise. In addition, image segmentation can reduce the physical size of the data set and hence processing times (xiv) – a relevant issue in regard to high resolution time series. In the presented study the applicability of SVM for the classification of multi-temporal SAR data is investigated. Different levels of image segmentation are generated and classified without using any segment specific features like segment size, shape etc., to investigate the impact of generalization as conducted during the segmentation process on the SVM performance and classification accuracy. The results of the SVMs are compared to classification results achieved by self-learning decision trees.

DATA SET AND PREPROCESSING

The nearly flat study site is located near Bonn, in the German state North Rhine-Westphalia. The area is dominated by agriculture and characterized by typical spatial patterns and temporal variation caused by differences in the crop phenology. The field plot size varies between approximately 3 and 5 ha, with cereals and sugar beets being the main crops. A dataset of 14 images from 9 acquisition dates, containing 5 Envisat ASAR alternating polarization and 4 ERS-2 precision images was used (Table 1). Thus, the data set comprised information from varying phenological stages and different polarizations. In addition, a Landsat 5 TM image was available, which was used for the image segmentation. A map from a detailed field survey was used for generating the training and validation sample sets.

An orthorectification of the Landsat image was performed, using a digital elevation model. The SAR imagery was calibrated to backscatter intensity following a common procedure. Subsequently all data sets were co-registered and an enhanced Frost filter was applied to reduce the speckle. Finally the SAR images were orthorectified using a digital elevation model, orbit parameters and the corrected Landsat image as reference data set.

Table 1: Multi-temporal SAR Data set

Sensor	Date	Track / Swath	Polarization	Orbit
ASAR	12-Apr-05	6208	HH / HV	asc
ERS-2	21-Apr-05	337	VV	des
ERS-2	26-May-05	337	VV	des
ERS-2	30-Jun-05	337	VV	des
ASAR	13-Jul-05	3029	HH / HV	asc
ASAR	22-Jul-05	7158	HH / HV	asc
ERS-2	4-Aug-05	337	VV	des
ASAR	14-Aug-05	2487	HH / HV	asc
ASAR	18-Sep-05	2487	HH / HV	asc

Although several segmentation methods have been developed for SAR data, segmentation is still difficult due to the speckle. Outlines derived from optical data seem more appropriate (xv). Hence a segmentation of the Landsat image was performed. Afterwards the segment outlines were transferred onto the SAR data set. Several techniques for image segmentation of optical data sets exist (xvi,xvii,xviii). Region-growing methods assume that pixels of the same natural feature have a certain spectral homogeneity. In this study the commonly available region-growing approach by Baatz and Schäpe (xvii) was used.

In the initial phase of the process, pixels are handled as individual segments, which are iteratively merged into larger segments. Candidate pairs of adjacent segments are found by local mutual best fitting. The difference between the heterogeneity of a possible new segment compared to that of its two constituent segments is used as a stopping criterion for the region-growing. If it exceeds a user defined value, the growing process stops. In the presented study only the spectral information was used to estimate the segments' heterogeneity. In doing so the segments were not constrained to any pre-defined shape. To investigate the impact of the segmentation on classification accuracy three different image segmentations were generated. By computing each of the three aggregation levels (*scale 1-3*) separately, all segmentations were independent from the prior result. The average segment size of *scale 1* was 10 pixels (~0.9 ha), of *scale 2* 25(~2.2 ha) and 65 of *scale 3* (~5.8 ha).

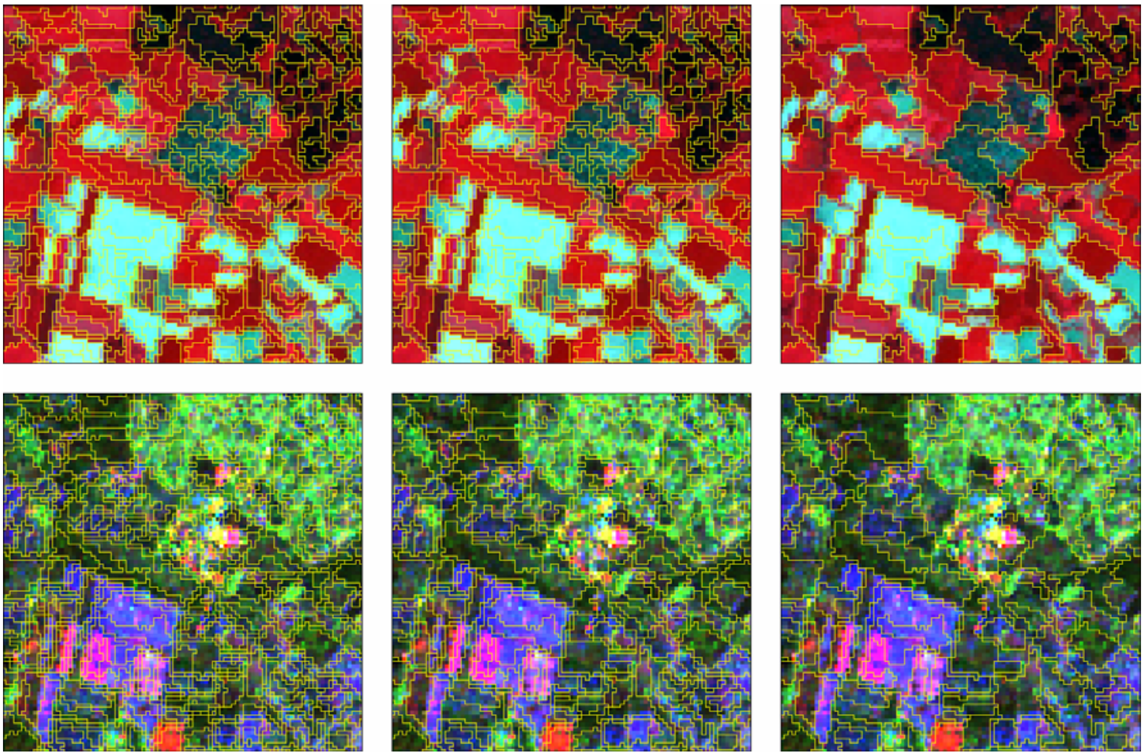

Figure 1: Landsat 5 TM (4,3,2) and multi-temporal SAR images with segment outlines from TM data. Average segment size 10 pixels, 25 pixels and 65 pixels (from left to right).

METHODS

SVM delineate two classes by fitting an optimal separating hyperplane to the multi-dimensional feature space. This optimization bases on structural risk minimization and tries to maximize the margin between the hyperplane and the closest training data points, the so-called support vectors. Thus, SVM only consider training samples close to the class boundary and might work well with small sample sets (xix). For linearly not separable classes the input data are mapped into a high dimensional space wherein the newly spread data point distribution enables the fitting of a linear hyperplane. A detailed description on the general concept of SVM is given in Vapnik (xx) and Burges (xxi). Comprehensive introductions in a remote sensing context are given by Huang et al. (vii) or Foody & Mathur (viii).

The binary nature of the SVM requires a useful strategy to solve a multi-class problem (viii). Two main approaches exist: the one-against-one strategy (OAO) and the one-against-all strategy (OAA). OAO applies a set of individual classifiers to all possible pairs of classes and performs a majority vote to assign the winning class. In the case of OAA, a set of binary classifiers is trained to separate each class from the rest. The maximum decision value determines the final class label. In this work, the OAO strategy was performed. A Gauss kernel was used for the training of the SVM. The training parameters were set following the leave-one-out cross validation approach *Looms* by Lee & Lin (xxii).

For the generation of training and validation data sets an extensive ground truth campaign was conducted in summer 2005. A training data set can be generated in different ways: e.g. simple random sampling, systematic sampling or stratified random sampling. Using the first method, each sample has an equal chance to be selected, the systematic approach selects samples with an equal interval over the study area. Stratified random sampling combines a priori knowledge about a study area – like land cover information – with the simple random sampling approach (xxiii). Using land cover classes as a priori knowledge, the stratified random sampling guarantees, that all classes are included in the sample set. In the presented study two sample sets for 6 classes are generated with an equalized random sampling (cereals, forest, grassland, orchard and root crops). In doing so each class has the same sample size, containing 50 or 100 samples per class, respectively. Using the same methodology as before, an independent validation set was generated, containing 1560 samples, 260 of each class. Using this independent sample set, the total accuracy and the kappa coefficient are calculated for the accuracy assessment.

The results of the SVM approach are compared to the outputs of a self-learning decision tree. The handling of DTs is relatively simple and they are not constrained to assumptions like normal distribution of input data. Unlike SVM the training time is relatively low and no complex parameter fitting is necessary. In the presented study the decision tree algorithm see5 (xxiv) is used. This approach was used successfully in several studies for classifying optical and SAR data (ii,vi,xxv).

RESULTS & DISCUSSION

The accuracy assessment shows the positive effect of image segmentation on the classification accuracy of the SAR data (Table 2). Using an adequate aggregation scale the classification accuracy is increased. With the smaller sample set, for example the accuracy of 50% on pixel level is increased up to 76% at scale 1. A further improvement up to 78% is achieved by scale 2. Indeed the scale of aggregation is crucial and a coarse segmentation is leading to reduced classification accuracy. Using scale 3 the classification accuracy drops below the accuracy achieved by the smallest aggregation size. A larger sample set can slightly improve the classification accuracy.

The accuracy assessment shows that in case of segmented data support vector machines lead to better results than simple decision trees (Table 2). The best accuracy of a decision tree is 75.5%, the corresponding SVM achieves an accuracy of 78.2% (training set 100 – scale 2). But the decision tree outperforms the support vector machines on pixel data. Maybe the decision tree can handle the noisy data more effective than the SVM approach does. The impact of image segmentation on the accuracy achieved by the decision tree is comparable to the findings for SVM.

Table 2: Total accuracy and kappa of the support vector machine and decision tree classification or pixel image and segmented data

Averaged segment size	SVM training set 50	SVM training set 100	DT training set 50	DT training set 100
Pixel	50.3 / 0.40	54.6 / 0.45	55.0 / 0.46	59.7 / 0.52
~10 pixels	75.9 / 0.71	76.9 / 0.72	72.1 / 0.67	71.7 / 0.66
~25 pixels	77.8 / 0.73	78.2 / 0.74	70.8 / 0.65	75.5 / 0.71
~65 pixels	71.7 / 0.66	73.5 / 0.68	70.8 / 0.65	67.9 / 0.62

The visual inspection of classification outputs is in accordance with the statistical evaluation. The quality of the derived maps is significantly increased by the segmentation of the data (Figure 2). This can be explained by the removal of data inherent noise and outliers. Within the classified pixel image only large regions can be clearly distinguished. The differentiation between smaller natural structures like field plots seems difficult. Comparing the maps from different aggregation levels, the one with the largest segments is easiest to perceive and appears most homogeneous. However the statistical evaluation showed that scale 3 was worse than scale 2 and scale 1. A comparison to the reference map shows that a possible false assignment of an individual segment leads to the misclassification of a large area. This typical drawback of segment-based analysis is particularly obvious for scale 3, where several segments include more than one filed plot.

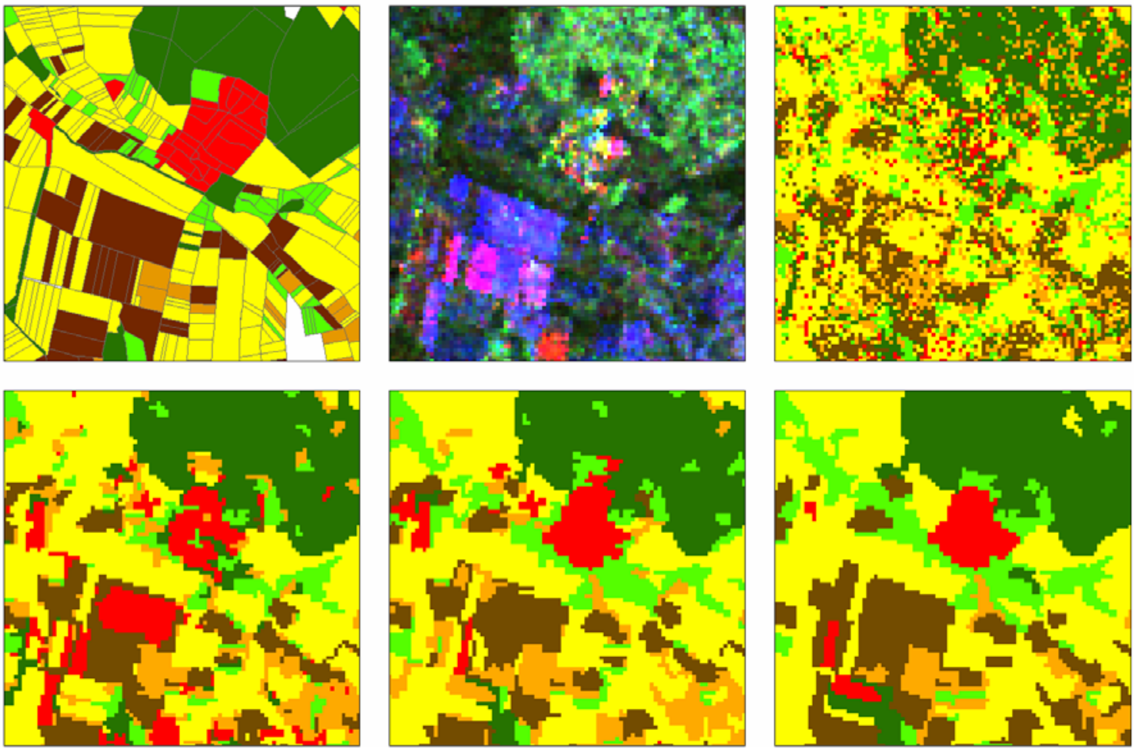

Figure 2: Land cover map, multi-temporal SAR data, pixel-based SVM classification (upper row) and classification results based on three different scales.

SUMMARY & CONCLUSIONS

SVM have been successfully used for the classification of segmented multi-temporal SAR data. Results are slightly better than those from a DT. A significant positive influence of image segmentation on the overall accuracy could be observed for all classification levels. In regard to the decreasing accuracy when segments become too large, the use of segments that are slightly smaller than natural objects seems appropriate, instead of trying to match original outlines. In the presented study a mean segment size of 25 pixels is appropriated.

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REFERENCES

i. Foody G M & M K Arora, 1997. An evaluation of some factors affecting the accuracy of classification by an artificial neural network. International Journal of Remote Sensing, 18: 799-810

ii. Pal M & P M Mather, 2003. An assessment of the effectiveness of decision tree methods for land cover classification. Remote Sensing of Environment, 86: 554-565

iii. Del Frate F, G Schiavon, D Solimini, M Borgeaud, D H Hoekman & M A M Vissers, 2003. Crop classification using multiconfiguration C-band SAR data. IEEE Transactions on Geoscience and Remote Sensing, 41: 1611-1619

iv. Chust G, D Ducrot & J L Pretus, 2004. Land cover discrimination potential of radar multitemporal series and optical multispecral images in a Mediteranean cultural landscape. International Journal of Remote Sensing, 25 : 3513-3528

v. Benediktsson J A, P H Swain & O K Ersoy, 1990. Neural Network Approaches Versus Statistical Methods In Classification Of Multisource Remote Sensing Data. IEEE Transactions on Geoscience and Remote Sensing, 28: 540-552

vi. Friedl M A & C E Brodley, 1997. Decision Tree Classification of Land Cover from Remotely Sensed Data. Remote Sensing of Environment, 61: 399-409

vii. Huang C, L S Davis J R G Townshend, 2002. An assessment of support vector machines for land cover classification. International Journal of Remote Sensing, 23: 725-749

viii. Foody G M & A Mathur. 2004. A Relative Evaluation of Mulitclass Image Classification of Support Vector Machines. IEEE Transactions on Geosciences and Remote Sensing, 42: 1335-1343

ix. Lardeux C, P L Frison, J P Rudant, J C Souyris, C Tison, B Stoll, 2006. Use of the SVM classification with polarimetric SAR data for Land use carthography. In: Geoscience and Remote Sensing Symposium 2006 (IGARSS ’06, Denver), in print.

x. Fukuda S & H Hirosawa, 2001. Support Vector Machine Classification of Land cover: Application to Polarimetric SARdata. In: Geoscience and Remote Sensing Symposium 2001 (IGARSS ’01 WO), 187-189

xi. Tso B & RM Mather, 1999. Crop discrimination using multi-temporal SAR imagery. International Journal of Remote Sensing, 20: 2443-2460

xii. Shackelford A K & C H & Davis, 2003. A Combined Fuzzy Pixel-Based and Object-Based Approach for Classification of High-Resolution Multispectral Data Over Urban Areas. *IEEE* Transactions on Geosciences and Remote Sensing, 41: 2354-2363

xiii. Song M, D L Civco & J D Hurd, 2005. A competitive pixel-object approach for land cover classification. International Journal of Remote Sensing, 26: 4982-4997

xiv. Schiefer S, P Hostert, E Diermayer & A Damm, 2005. Compression and object-oriented processing of segmented hyperspectral images in ENVI. In: Proc. 4th EARSeL Workshop on Imaging Spectroscopy, Warsaw, edited by B. Zagajewski & M. Sobczak, 609-616.

xv. Lombardo P, C J Oliver, T M Pellizzeri & M Meloni, 2003. A New Maximum-Likelihood Joint Segmentation Technique for Multitemporal SAR and Multi Optical Images. IEEE Transactions on Geoscience and Remote Sensing, 41: 2500-2518

xvi. Le Moigne J & J C Tilton, 1995. Refining image segmentation by integration of edge and region data. IEEE Transactions on Geoscience and Remote Sensing, 33: 605-615

xvii. Baatz M & A Schäpe, 2000. Multiresolution Segmentation - an optimization approach for high quality multi-scale segmentation. In: Angewandte Geogr. Informationsverarbeitung XII, edited by J Strobel et al. (Beiträge zum AGIT-Symposium Salzburg)

xviii. Evans C, R Jones, I Svalbe & M Berman, 2002. Segmenting Multispectral Landsat TM Images Into Field Units. IEEE Transactions on Geoscience and Remote Sensing, 40: 1054-1064

xix. Foody G M & A Mathur, 2006. The use of small training sets containing mixed pixels for accurate hard image classification: Training on mixed spectral responses for classification by a SVM. Remote Sensing of Environment, 103: 179-189

xx. Vapnik V N, 1995. The Nature of Statistical Learning Theory. (Springer Verlag, New York)

xxi. Burges C J C 1998: A Tutorial on Support Vector Machines for Pattern Recognition. Data Mining and Knowledge Discovery, 2: 121-167

xxii. Lee J H & C J Lin, 2000. Automatic model selection for support vector machines, Technical report, Dept. of Computer Science and Information Engineering, National Taiwan University, http://www.csie.ntu.edu.tw/~cjlin/looms/

xxiii. Congalton R G & K Green, 1999. Assessing the Accuracy of Remote Sensed Data: Principles and Practices, (Lewis Publishers)

xxiv. Quinlan J R, 1993. Programs for Machine Learning, (San Fransisco, CA: Morgan Kaufmann)

xxv. Simard M, G de Grandi, S Saatchi & P Mayaux, 2002. Mapping tropical coastal vegetation using JERS-1 and ERS-1 radar data with a dwcision tree classifier. International Journal of Remote Sensing, 23: 1461-1474