52. IWK

Internationales Wissenschaftliches Kolloquium
International Scientific Colloquium

PROCCEDINGS | 10 - 13 September 2007

FACULTY OF COMPUTER SCIENCE AND AUTOMATION

COMPUTER SCIENCE MEETS AUTOMATION

VOLUME II

Session 6 - Environmental Systems: Management and Optimisation
Session 7 - New Methods and Technologies for Medicine and Biology
Session 8 - Embedded System Design and Application
Session 9 - Image Processing, Image Analysis and Computer Vision
Session 10 - Mobile Communications
Session 11 - Education in Computer Science and Automation

TECHNISCHE UNIVERSITÄT
ILMENAU

Bibliografische Information der Deutschen Bibliothek
Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbiografie; detaillierte bibliografische Daten sind im Internet über **http://dnb.ddb.de** abrufbar.

ISBN 978-3-939473-17-6

Impressum

Herausgeber: Der Rektor der Technischen Universität Ilmenau
Univ.-Prof. Dr. rer. nat. habil. Peter Scharff

Redaktion: Referat Marketing und Studentische Angelegenheiten
Kongressorganisation
Andrea Schneider
Tel.: +49 3677 69-2520
Fax: +49 3677 69-1743
e-mail: kongressorganisation@tu-ilmenau.de

Redaktionsschluss: Juli 2007

Verlag:
Technische Universität Ilmenau/Universitätsbibliothek
Universitätsverlag Ilmenau
Postfach 10 05 65
98684 Ilmenau
www.tu-ilmenau.de/universitaetsverlag

Herstellung und Auslieferung: Verlagshaus Monsenstein und Vannerdat OHG
Am Hawerkamp 31
48155 Münster
www.mv-verlag.de

Layout Cover: www.cey-x.de

Bezugsmöglichkeiten: Universitätsbibliothek der TU Ilmenau
Tel.: +49 3677 69-4615
Fax: +49 3677 69-4602

Preface

Dear Participants,

Confronted with the ever-increasing complexity of technical processes and the growing demands on their efficiency, security and flexibility, the scientific world needs to establish new methods of engineering design and new methods of systems operation. The factors likely to affect the design of the smart systems of the future will doubtless include the following:

- As computational costs decrease, it will be possible to apply more complex algorithms, even in real time. These algorithms will take into account system nonlinearities or provide online optimisation of the system's performance.
- New fields of application will be addressed. Interest is now being expressed, beyond that in "classical" technical systems and processes, in environmental systems or medical and bioengineering applications.
- The boundaries between software and hardware design are being eroded. New design methods will include co-design of software and hardware and even of sensor and actuator components.
- Automation will not only replace human operators but will assist, support and supervise humans so that their work is safe and even more effective.
- Networked systems or swarms will be crucial, requiring improvement of the communication within them and study of how their behaviour can be made globally consistent.
- The issues of security and safety, not only during the operation of systems but also in the course of their design, will continue to increase in importance.

The title "Computer Science meets Automation", borne by the 52nd International Scientific Colloquium (IWK) at the Technische Universität Ilmenau, Germany, expresses the desire of scientists and engineers to rise to these challenges, cooperating closely on innovative methods in the two disciplines of computer science and automation.

The IWK has a long tradition going back as far as 1953. In the years before 1989, a major function of the colloquium was to bring together scientists from both sides of the Iron Curtain. Naturally, bonds were also deepened between the countries from the East. Today, the objective of the colloquium is still to bring researchers together. They come from the eastern and western member states of the European Union, and, indeed, from all over the world. All who wish to share their ideas on the points where "Computer Science meets Automation" are addressed by this colloquium at the Technische Universität Ilmenau.

All the University's Faculties have joined forces to ensure that nothing is left out. Control engineering, information science, cybernetics, communication technology and systems engineering – for all of these and their applications (ranging from biological systems to heavy engineering), the issues are being covered.

Together with all the organizers I should like to thank you for your contributions to the conference, ensuring, as they do, a most interesting colloquium programme of an interdisciplinary nature.
I am looking forward to an inspiring colloquium. It promises to be a fine platform for you to present your research, to address new concepts and to meet colleagues in Ilmenau.

Professor Peter Scharff
Rector, TU Ilmenau

Professor Christoph Ament
Head of Organisation

Table of Contents

C O N T E N T S

Page

6 Environmental Systems: Management and Optimisation

10 Mobile Communications

11 Education in Computer Science and Automation

B. Waske / V. Heinzel / M. Braun / G. Menz

Classification of Segmented SAR and Multispectral Satellite Imagery using Support Vector Machines

INTRODUCTION

The detailed knowledge of land cover is an important input parameter in several environmental monitoring and decision support systems. Earth-observation (EO) systems have the potential to provide spatially distributed, near-real time information on land cover and its environmental state at various spatial scales.

Land cover classifications are one of the main applications in the field of remote sensing and in several applications different data sources are combined, e.g., synthetic aperture radar (SAR) and optical imagery. In doing so the overall classification accuracy can be significantly increased compared to the quality of a single-source application [1]-[4].

Today the number of various passive and active EO-systems is increasing (e.g. multispectral and SAR), operating at different wavelengths ranging from the visible to microwave. Consequently complementary land cover information can be acquired and multisensor approaches become even more attractive. Hence, an adequate data fusion and classification of multisource imagery is an important ongoing research topic in the field of remote sensing.

Widely used statistical approaches seem inefficient, because often such imagery cannot be modeled by an adequate multivariate statistical model. Hence non-parametric methods as for example support vector machines (SVM), artificial neural networks and decision trees seem more applicable. In several studies multisource data have been classified by *decision fusion* [1], [2], [5], which is a strategy of combining different information, after each individual source has been classified previously. In Waske and Benedisktsson [2] a SVM-based decision fusion was applied to SAR and multispectral data. Instead of applying the classifier directly to a multisource data set, each image source was classified separately. The outputs of the SVM were combined by different concepts to create the final classification map. Besides different voting schemes the decision fusion was performed by another SVM, which was trained on the outputs of the two individual SVM classifiers. This strategy outperforms conventional voting methods as well as other parametric and nonparametric classifiers as a single SVM, which was applied directly to the full multisource data set.

A conceptual approach in classifying remote sensing imagery is that of segment-based classifications, where usually adjacent pixels with similar properties are merged into segments, before the classification is applied. In doing so, additional information as segments' mean value as well as neighborhood relationships can be derived and used during the classification process. Segment-based methods are particularly interesting for agricultural areas that are characterized by typical spatial patterns of planted crops. Moreover such concepts can solve two common problems, which are often arising in pixel based classifications [6], [7]: Site-internal variations in spectral reflectance or backscatter intensity, which might be caused due to within-field heterogeneities (e.g., soil moisture, plant infections etc.), will be eliminated during image segmentation. In addition the negative impact of mixed pixels, which occurs along the boundaries of two objects, can be reduced by averaging the pixel values within the segment. In regard to SAR imagery and the data inherent speckle, image segmentation has the positive effect that the speckle is leveled out [8].

In the presented study, we evaluate the concept of fusing individual outputs of SVM [2] on multitemporal SAR and multispectral data that have been previously segmented. The fused classification is compared to single-source results and that of a single SVM, which is applied on the whole multisource data set.

DATA SET AND PREPROCESSING

The test site is located near Bonn in the German state North Rhine-Westphalia. The area is primarily used for agriculture. In this study a multisensor data set was available, containing multitemporal SAR data and a multspectral Landsat 5 TM image from May 28, 2005. The SAR data set includes 9 ENVISAT ASAR and ERS-2 acquisitions with different polarizations over the period April to September, 2005. The remote sensing imagery was pre-processed following common procedures. Finally image segmentation was applied separately for the multitemporal SAR data and the Landsat image (see Figure 1). In this study a commonly available approach was used that is based on a region-growing algorithm [9] and the pixel value only was used as controlling criterion for the segmentation procedure. To omit errors due to segmentation, relatively small segments were generated (~10 pixel). The segment mean values were derived and used in the subsequent classification process.

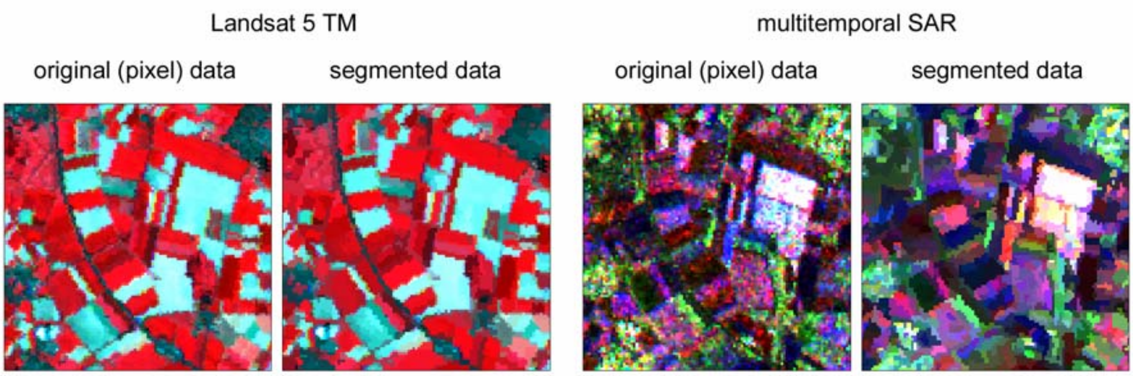

Figure 1: original and segmented Landsat 5 TM (band 4-3-2) and SAR data (21-Apr/26-May/30-Jun.)

METHODS

Support Vector Machines

SVM differentiate two classes by fitting an optimal linear separating hyperplane (OSH) to the samples in a multi-dimensional feature space. The optimization problem is based on structural risk minimization and aims to maximize the margins between the OSH and the closest samples (i.e., the support vectors) [10]. In a linearly not separable case, the input data are mapped into a higher dimensional feature space. Thus, a linear hyperplane can be fit to the newly distributed samples. In contrast to other classifiers (e.g. decision trees), which directly assign a class label to an unknown pixel, the output images of SVM contain the distance between each pixel and the hyperplane of the binary classification problem, from now on referred to as *rule images*. These rule images are used to determine the final class membership. An introduction on the general concept of SVM is given by Schölkopf and Smola [11].

SVM have originally been developed for binary classification problems, which normally do not exist in the context of remote sensing image classifications. In the literature, different approaches have been introduced to solve multi-class problems. Usually a *n*-class classification problem is split into several binary sub-problems and the individual binary SVM are combined into a classifier ensemble. Two main multi-class strategies exist: the one-against-one strategy (OAO) and the one-against-all strategy (OAA):

For the OAA approach, *n* binary classifiers are trained to differentiate each individual class from the remaining classes. The maximum distance to the hyperplane determines the final class membership. In case of the OAO concept one SVM for each possible pair-wise classification problem is applied, resulting in a set of $n(n-1)/2$ binary classifiers. The final class membership is predicted by a simple majority vote, using the simple sign of the distance to the hyperplane. Even the OAO concepts results in more binary SVM classifiers, the classification problem is divided in many problems that are simpler.

Decision Fusion and Classification
Eight land cover classes were considered in the classification experiment: *Arable crops*, *Cereals*, *Forest*, *Grassland*, *Orchards*, *Rapeseed*, *Root crops* and *Urban*. For each land cover class 150 samples were randomly selected from the ground truth information, by equalized random sampling. In addition an independent validation set with 500 samples per class was generated. Using the same training samples the SVM were trained on three data sets: (1) Landsat image, (2) multitemporal SAR data, and (3) a multisensor data set.

The OAO strategy was used to solve the multi-class problem, using a set of SVM classifiers with optimized parameters for γ and C. In this study a Gaussian kernel was used [10], which is a common kernel function in context of remote sensing. The training of the SVM and the generation of the rule images were performed using *imageSVM* [12]. *imageSVM* is a freely available IDL/ENVI implementation that is based on the LIBSVM approach by Chen and Lee [13] for the classifier training. Ideal values for γ and C were selected from a user defined range of possible parameters based on 10-fold cross validation. Beside the classification of the whole multisensor data set, the proposed technique is applied, fusing the individual rule images by another SVM.

Using the independent validation set, the accuracy assessment is performed on a pixel-basis, calculating the overall and class-specific accuracies.

RESULTS

The experiments results clearly demonstrate the positive impact of multisensor imagery. Whereas the single-source classifiers achieve overall accuracies of 73.3% and 73.9% respectively, the application of a SVM on a multisource data set improves the results up to 79.1%. The multisource results can be further increased by the proposed fusion methods. By a separate training of the SVM on the two image source and a subsequent fusion of the outputs by another SVM the overall accuracy can be increased up to 80.9%.

Compared to pixel-based classification results (not presented in detail) the image segmentation increase the overall accuracies at least by up to 3% and even up to 11% when compared to the accuracy achieved with the SAR imagery alone.

The assessment of the class-specific accuracies (i.e., producer and user accuracies) illustrates the different nature of the image types. Some classes are better differentiated by the SAR imagery (e.g., *grassland, orchards*), whereas other classes are classified more accurate by the multispectral data (e.g., *arable crops, urban*). In addition the efficiency of multisensor application is more than confirmed (Table 2).

Table 1: Overall accuracy [%]

Data set / Method	Overall accuracy
SAR	73.3
TM	73.9
SAR + TM	79.1
SVM fusion	80.9

Table 2: Class-specific accuracy, using a single SVM and the proposed fusion strategy

Land cover class	Producer accuracy			User accuracy		
	SAR	*TM*	*SVM Fusion*	*SAR*	*TM*	*SVM Fusion*
Arable crops	65.2	67.2	73.8	70.7	75.0	81.8
Cereals	81.0	79.2	81.4	64.4	70.6	76.1
Forest	88.0	92.2	95.0	82.2	94.6	95.6
Grassland	71.6	61.4	75.0	72.9	63.9	73.3
Orchard	72.4	58.2	77.4	68.8	59.6	73.3
Rapeseed	69.2	72.0	82.2	78.1	79.6	82.7
Root crops	71.0	77.0	78.6	68.3	64.1	76.6
Urban	68.0	84.0	82.6	86.1	86.9	88.4

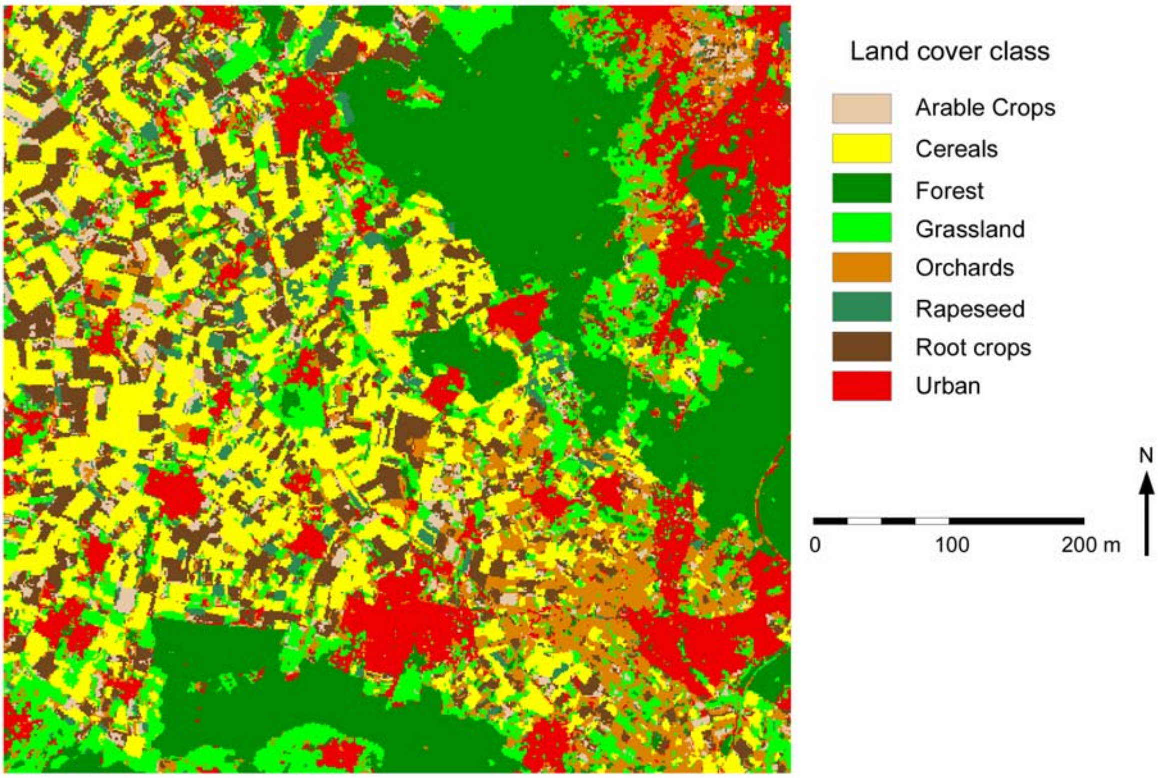

Figure 2: Classification results, using the proposed fusion strategy

CONCLUSION

A concept of fusing multisensor imagery was evaluated. It has been shown that the concept, which was originally developed on pixel-based data, is appropriate for segmented imagery. The different nature of the data, i.e., the multispectral image and the SAR data, is one reason for the success of the proposed classifier strategy.

Both sources provide different information and may not be equally reliable. Instead of using one specific kernel function for the whole multisource data set, the definition of separate kernel functions for each data source seems more adequate.

In general the results demonstrate the positive effect of multisensor imagery, and the classification accuracy is significantly increased by such data sets. This is particularly relevant with respect to recent and upcoming EO missions like, ALOS, TerraSAR-X and Radarsat-2.

ACKNOWLEDGEMENTS

The authors wish to thank the European Space Agency for providing Envisat ASAR and ERS-2 data through a CAT 1 proposal (C1.3115). The data were acquired within the ENVILAND research project (FKZ 50EE0404), funded by the German Aerospace Center (DLR) and the Federal Ministry of Economics and Technology (BMWi).

References:

[1] J.A. Benediktsson and I. Kanellopoulos (1999): Classification of Multisource and Hyperspectral Data Based on Decision Fusion. *IEEE Trans. Geosci. and Remote Sens*., vol. 37, pp. 1367-1377.

[2] B. Waske and J. A. Benediktsson (2007): Fusion of Support Vector Machines for Classification of Multisensor Data. *IEEE Trans. Geosci. and Remote Sens*., *in press*.

[3] X. Blaes, L. Vanhalle, and P. Defourny (2005): Efficiency of crop identification based on optical and SAR image time series. *Remote Sens. of Env*., vol. 96, pp. 352-365.

[4] G. Chust, D. Ducrot, and J.L. Pretus (2004): Land cover discrimination potential of radar multitemporal series and optical multispectral images in a Mediterranean cultural landscape. *Int. J. of Remote Sens.*, vol. 25, pp. 3513-3528.

[5] J.A. Benediktsson, J. R. Sveinsson, and P. H. Swain (1997): Hybrid Consensus Theoretic Classification. *IEEE Trans. Geosci. and Remote Sens*., vol. 35, pp. 833-843.

[6] G.M. Smith and R.M. Fuller (2001): An integrated approach to land cover classification: an example in the Island of Jersey. *Int. J. of Rem. Sens*.. vol. 22, pp. 3123-3142.

[7] J.W. De Wit and J. Clevers (2004): Efficiency and accuracy of per-filed classification for operational crop mapping. *Int. J. of Rem. Sens.*, vol. 20, pp. 4091-4112.

[8] B. Tso and R.M. Mather (1999): Crop discrimination using multi-temporal SAR imagery. *Int. J. of Remote. Sens*., vol. 20, pp. 2443-2460.

[9] M. Baatz and A. Schäpe (2000): *Multiresolution Segmentation - an optimization approach for high quality multi-scale segmentation.* In: J. Strobel et al. (Eds.): Angewandte Geogr. Informationsverarbeitung.

[10] V.N. Vapnik (1998): *Statistical Learning Theory*, New York: Wiley.

[11] B. Schölkopf and A. Smola (2002): *Learning with Kernels*, MIT Press, Cambridge, MA.

[12] Janz, S. Schiefer, B. Waske, and P. Hostert (2007): A user-oriented tool for advanced classification of hyperspectral data using support vector machines. *5th Works. EARSeL Special Interest Group on Imaging Spectroscopy*, Bruges, Belgium.

[13] C.-C. Chen, and C.-J. Lin (2001): *LIBSVM: a library for support vector machines*. Software available at: http://www.csie.ntu.edu.tw/~cjlin/libsvm.

Authors:

Björn Waske, V. Heinzel , M. Braun, and G. Menz
Center for Remote Sensing of Land Surfaces (ZFL)
University of Bonn, Walter-Flex-Str. 3, 53113, Bonn
Phone: +49-228-734941
Fax: +49-228-736857
E-mail: bwaske@uni-bonn.de