SEMIAUTOMATIC CLASSIFICATION PROCEDURES FOR FIRE MONITORING USING MULTITEMPORAL SAR IMAGES AND NOAA-AVHRR HOTSPOT DATA

G. Willhauck [*], U. Benz [*], F. Siegert [**]

[*] DEFINIENS AG
Trappentreustrasse 1, 80339 Munich, Germany

[**] RSS GMBH
Wörthstraße 49, 81667 Munich, Germany

ABSTRACT

Large scale fire monitoring using remote sensing imagery is an important environmental task. Following the severe wildfires of 1997/98 in Indonesia, the need for an operational monitoring system became obvious. Based on object oriented image analysis techniques an application was implemented to generate fire damage maps out of a combination of ERS SAR images, vegetation maps and NOAA-AVHRR hotspot data. The application uses a modular approach which distinguishes classification rules based on pixel values from spatial ones and thereby allows the user to easily adapt the analysis routine to new input data if necessary. An XML based Wizard guides the analyst through the classification process and allows even an untrained user to handle the software. This way a monitoring application was generated, which allows to quickly produce the needed information.

1 INTRODUCTION

1.1 PROJECT DESCRIPTION AND BACKGROUND

In the last two decades, forest fires became the prevalent source of deforestation in tropical areas. This development, also greatly affected Indonesian forests. Due to the practice of selective logging, millions of tons of highly flammable biomass is left in the forests [1]. Following El Niño were month long dry periods, which in combination with carelessness with the traditional practice of fire clearance, caused large forest fires. The Asian Development Bank [2] estimated that the damages caused by the fire totaled 9 billion $US in 1997. The effects on the tropical ecosystem as well as global effects on weather are largely unknown.

In this context, the research project "CLAPS" funded by the DLR (German Space Agency) had as an objective to develop and test a procedure for supervised classification of satellite SAR images, which is suited for large scale burn scar mapping. Major criteria for this project was to operationalize the mapping process to enable an efficient use for large areas. The object oriented software eCognition, which performs an image segmentation before classification was chosen for this task to overcome speckle effects. Similar approaches to cope with speckle effect have been taken by Y. Dong [3].

1.2 STUDY AREA

The project area covers approx. 10,000 km^2 in the province Kalimantan Timur on the island of Borneo, Indonesia. The location of the scene was chosen as being representative for most vegetation and land use types in Kalimantan Timur. Furthermore major fire events occurred in this region in 1998. The scene covers also the GTZ/IFFM fire management project area. Extensive ground knowledge acquired during three field surveys (1996, 1998, 1999) is available from this area. Before the fires the vegetation was dominated by degraded lowland *Dipterocarp* forest and yet pristine (peat) swamp forest. All *Dipterocarp* forests in the project area had already been subjected to selective logging in the past. Shifting cultivation prevails close to the rivers. Several large pulp wood and oil plantations were established in the last decade.

2 MATERIAL AND METHODS

2.1 DATA

The analysis was based on multitemporal ERS SAR data because all optical satellite imaging systems were severely hampered by clouds, haze and smoke during the fires and rainy weather following the drought. Active microwave systems like ERS-2 and the recently launched ENVISAT are able to penetrate clouds and haze. Four single scenes (frame 3609) as well as 10 scenes (frame 3600/3618) covering a period from August 97 to November 98 were available. NOAA-AVHRR HS data served as an additional source of information during the classification process to reduce drought related errors [4]. An area was considered as burned only when there was 1.) a clear decrease in backscatter or 2.) a weak decrease in backscatter in conjunction with NOAA-AVHRR hot spots. NOAA data was regularly processed during the drought by the Integrated Forest Fire Management Project (IFFM) und Sustainable Forest Management Project (SFMP) in Indonesia, which were also contributing to the definition of the project requirements. Since the correct classification of water areas and the differentiation of vegetation types was not possible based on radar imagery, additional thematic layers representing water areas and the vegetation type were used.

2.2 RADAR IMAGE PROCESSING

Difference detection techniques applied to pairs of ERS-2 SAR images were used to map the burned area with high accuracy and to assess the level of fire damage from changes in image intensity and texture [5]. Pre- and post-fire images were co-registered to form bi-temporal image pairs. Co-registration was done automatically using the SAR Toolbox (ESA) with a registration error of less than one pixel. The images were calibrated to represent radar image backscatter, sub-sampled to 25 m pixel size, speckle filtered and georeferenced. The fire impact classification was done by visual on-screen interpretation of the bi-temporal radar imagery using a Geographic Information System at scale 1:200,000. The interpretation of SAR signatures was based on GPS mapped ground observations. The results of the visual interpretation served as reference to validate the object oriented image classification procedure presented in this paper.

2.3 OBJECT ORIENTED IMAGE ANALYSIS

2.3.1 General overview

The classification technique used follows the concept that important semantic information necessary to interpret an image is not represented in single pixels but in meaningful image objects and their mutual relations. Thus, the strategy delivers results noticeably better than conventional methods. Through the use of semantic information, classification tasks can be addressed which until now could not be managed by state-of-the-art software. This object oriented image analysis is based upon contiguous, homogeneous image regions which are generated by an initial image segmentation. Connecting all the regions, the image content is represented as a network of image objects. These image objects act as the building blocks for the subsequent image analysis. In comparison to pixels, image objects carry much more useful information. Thus, they can be characterized by far more properties than pure spectral or spectral-derivative information, such as their form, texture, neighborhood or context. Analyzing an image in eCognition means to classify the image objects according to class descriptions organized in an appropriate knowledge base. The knowledge base itself is created by means of inheritance mechanisms, concepts and methods of fuzzy logic, and semantic modeling.

2.3.2 Segmentation

A prerequisite to classification in the object oriented approach is an image segmentation. The segmentation used is a bottom up region-merging technique starting with one-pixel objects. In numerous subsequent steps smaller image objects are merged into bigger ones. The procedure simulates an even and simultaneous growth of segments over a scene in each step. It starts at an arbitrary point in the image with one-pixel objects. The algorithm guarantees a regular spatial distribution of treated image objects. The underlying patented algorithm is essentially a heuristic optimization procedure, which minimizes the average heterogeneity of image objects for a given resolution over the whole scene.

Heterogeneity itself is based not only on the standard deviation of image objects but also on their shape. Weighting between spectral and shape heterogeneity enables an adjusting of segmentation results to the considered application.

$h_{spectral} = \sum_c w_c \sigma_c$	Spectral homogeneity
$h_{cmpct} = \frac{l}{\sqrt{n}}$	Shape homogeneity compactness
$h_{smooth} = \frac{l}{b}$	Shape homogeneity smoothness

σc = standard deviation c
ωc = weight of layer
l = border length
n = number of pixels
b = bounding box

Figure 1: *segmentation homogeneity parameters*

The stop criterion for the region-merging process is given by the parameter „scale“ and can be edited by the user. It determines the maximum allowed overall heterogeneity of the segments. The larger the scale parameters for one data set, the larger are the image objects. For a given scale parameter, the size of the resulting objects depends on the data characteristics. To this end, for each type of data set and application, the scale parameter has to be adjusted. The created segments are the so-called image objects. For further details on the used segmentation see Baatz & Schäpe 2000 [6]

After the segmentation all image objects are automatically linked to a network in which each image object knows its neighbors, and which represents important context information for later analysis. Subsequently repeating the segmentation with a varying scale parameter creates a hierarchical network of image objects. Each image object knows its super-object and its sub-objects.

2.3.3 Segmentation Parameters

The goal for the segmentation was to have small areas of homogeneous pixel values represented on a fine scale. The courser level is segmented to represent larger homogeneous areas. The objects are to be as big as possible while still displaying small clearly visible structures. The segmentation parameters are determined empirically. For this application a two level approach was used to be able to actively use the speckle effect existent in radar images. This technique is described in paragraph 2.3.4. Level 1 is generated after level 2.

As input layers for the segmentation, radar data and thematic vegetation layer were used. The available hotspot information was used as additional information for the classification.

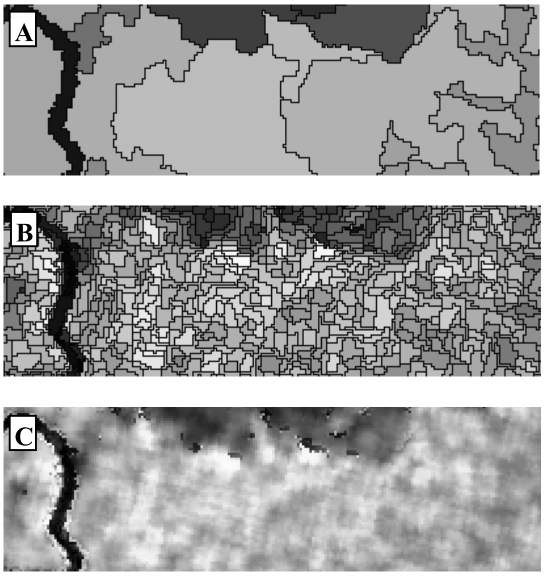

Figure 2: *Original image (C) and Segmentation results for level 1 (B) and level 2 (A). This segmentation leads to speckle reduction, without smearing edges. Thus, high radiometric and geometric resolution is obtained.*

2.3.3 Classification

The classification is based on fuzzy logic. Each class of a classification scheme contains a class description. Each class description consists of a set of fuzzy expressions allowing the evaluation of specific features and their logical operation. The output of the system is twofold: a fuzzy classification with detailed information of class mixture and reliability of class assignment, and a final crisp classification where each object is assigned to exactly one class (or none, if no assignment was possible).

A fuzzy rule can have one single condition or can consist of a combination of several conditions which have to be fulfilled for an object to be assigned to a class.

2.3.4 Classification approach

The strategy for fire damage classification is a two level approach, which utilizes information provided by small object primitives to label medium scale objects. Reason for this approach was that the setup of the class hierarchy should be easy to adapt, even for the non professional user. This is possible because the classification of the small object primitives can be easily performed based on samples without extensive ground truth knowledge. The small scale objects are separated into classes representing the basic available colors. The medium scale objects are separated into classes of different degree of damage based on their composition of sub objects and the additional information obtained from the vegetation and hotspot layers.

Class description level1: The basic classes "water", "corner", "blue", "brown" and "orange" are distinguished. The class names for the latter three are derived from the false color visualization and functions merely as a guideline for the image analyst.

The class "water" is classified based on the thematic information. The remaining objects of level 1 are classified based on their pixel values in the multitemporal PCA image data. Their purpose is to deliver basic information for the classification of level 2.

Class description level2: In this level, the actual classification of burned areas takes place. Several sources are used for the classification. The vegetation layer determines the type of burned forest and the possible variations of burn damage. The classification of the sub objects is used to determine the degree of the damage, a large amount of "blue" sub objects is characteristic for unburned or slightly burned areas. With an increasing amount of "orange" sub objects, the areas become more heavily damaged. Sub objects classified "brown" indicate old burned areas. Hotspot information is finally used to refine the results and avoid misclassification.

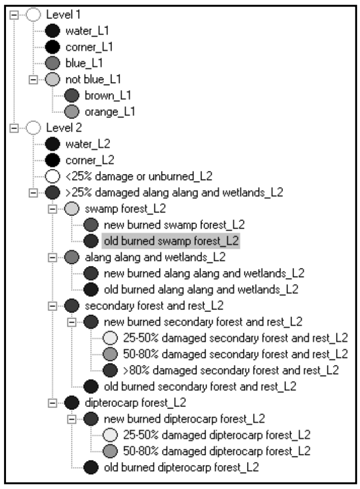

Figure 3: *class hierarchy*

2.4 AUTOMATION OF ANALYSIS

Automation of the analysis process is achieved with the software eCognition, which is used for the entire segmentation classification process. All major steps of the classification process were included in a protocol file and can automatically be applied to an image. As a part of this project, the protocol functionality was extended in a way, that inexperienced users can be guided through the different steps of the analysis process. This extension was implemented by creating an interface for XML scripts, which can trigger certain functionalities of the software as well as some especially generated menus. As a result, the user can start one application, which guides him through the entire application. Different selections are available depending whether the class hierarchy has to be adapted to differing input data or not.

3 CLASSIFICATION RESULTS AND ACCURACY ASSESSMENT

The classification result was compared to a manually delineated damage map and statistical information about the error was produced. The manually generated map shows a total burned area of 846738ha which equals 89,8% of the test area, while the result produced with eCognition classifies an area of 761227ha as burned, which equals 80.7%. A detailed comparison for the single damage classes is given in table 1. It can be observed, that for the low damage categories a higher consistency with the manual interpretation is reached. Especially the classification of swamp forests differs considerably. This can be explained with different survey periods between the two results. The data usable for classification covered a period from August 97 to April 98 whereas the manually produced results covered a period from August 97 to May 98. In those additional four weeks large parts of the swamp forests in the northwestern area of the test area were burned.

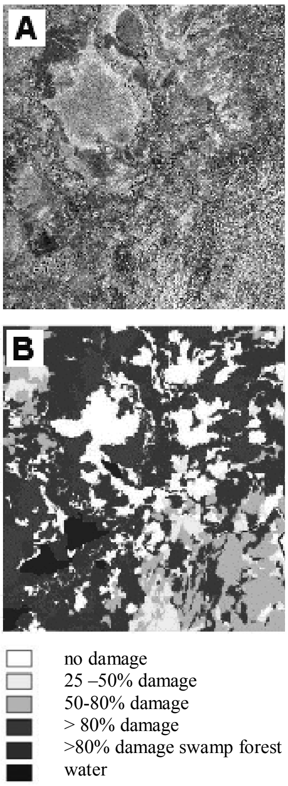

Figure 4: *PCA image (A) and classification result (B)*

	eCognition ha	eCognition %	Visual interpretation ha	Visual interpretation %
undamaged area	**181.568**	**19,3**	**96.052**	**10,2**
damage 25-50%	**70.351**	**7,5**	**69.166**	**7,3**
damage 50-80%	**155.055**	**16,4**	**223.533**	**23,7**
damage >80%	**154.142**	**16,3**	**272.966**	**29,0**
damage >80% (swamp forest)	**381.68**	**40,5**	**281.073**	**29,8**
Total	**942.794**	**100,0**	**942.79**	**100,0**

Table 1: *accuracy assessment results. Differences between visual interpretation results and eCognition results can partly be ascribed to different survey periods.*

4 CONCLUSIONS

The project showed that it is possible to develop eCognition classification strategies and implement them in an environment which allows operational application, even by non professionals. One major advantage was the software's capability for data fusion, which made the integration of various auxiliary data possible. The best classification results could be obtained for the total of the burned area. For the more detailed burn damage classification, additional data like hotspot data was found to greatly improve results. Even if the quality of this auxiliary data was of only mediocre quality (missing hotspots, large scale vegetation map) it was found to improve results. Having this data in higher quality would allow to also use the detailed damage classification in an operational setting. Unfortunately, part of the available ERS scenes was not usable, due to wet weather conditions. The classification process was designed in a way that it could be adapted to varying input data by assigning samples for the basic classes. Therefore this approach may also be transferred to images of other tropical regions or applied to advanced SAR data provided by ENVISAT.

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