Forest Classification of Multitemporal Mosaicked Satellite Images

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ABSTRACT

Experiences with the classification of forest condition in Carinthia, one of the nine federal provinces of Austria, are described. Three Landsat TM satellite scenes had to be mosaicked to cover all of Carinthia. Two such mosaicked scenes, one from June and one from August, were used for classification to take into account the different phenological stages of the forest. Additionally, the scenes were used to replace areas covered by clouds with cloud free data from the respective other scene. Very much effort was put into this classification project to receive knowledge on choosing classifieres – we tried a statistical and a neural network classifier – optimize the training process – true error rate approximation, generalization – and judge the final performance – statistical or human expert. Criteria for the final classification result was not only the true error rate but also the confusion matrix giving the desired importance for each class. An additional subjective criteria was the comprehensibility of the training and the classification results and the visual appearance of the classification border lines of the individual Landsat TM images of one scene of Carinthia.

KURZFASSUNG

Für das Bundesland Kärnten wurde eine flächendeckende Klassifikation des Waldzustandes aus Satellitenbilddaten durchgeführt. Um ganz Kärnten abdecken zu können mußten drei Landsat TM Szenen zu einem Mosaik zusammengesetz werden. Der Artikel beschreibt wesentliche Aspekte der Datenaufbereitung, der Merkmalsauswahl, der Klassifikation unter besonderer Berücksichtigung verschiedener Klassifikatoren, der Mosaikbildung aus mehreren Landsat TM Szenen sowie der Qualitätsbeurteilung der Klassifikationsergebnisse.

1 INTRODUCTION

In support of the forestry framework for the province of Carinthia a forest classification based on satellite images has been performed. This shall record the actual state of the forest for the whole province. Satellite images serve particularly well for this type of problem because they allow to derive forestry parameters that are not – or at least not in a suitable scale – available from maps or other sources. The parameters which had to be recorded by means of the classification were the actual edge of the forest, the forest type (4 classes), the stand age (3 classes), and the stand density (2 classes).

The classification results afterwards shall be integrated into a geographic information system (GIS) together with other information that is required for the forestry framework, such as digital elevation models (DEMs) and geological maps. There they shall be jointly processed and overlayed for planning and analysis purposes. In this connection the classification results present themselves as the most actual GIS layer.

The work steps necessary for realising the task and the employed methods shall be presented in the following exposition.

2 DATA SPECIFICATION

2.1 Satellite Data and DEM

The area to be classified covered approximately 15.000 km^2. Lansat TM data were suitable for giving an overview of the forest condition over such a large area. Furthermore, neither SPOT nor Russian KFA data was available with blanket coverage within an acceptable period. Therefore, the analysis was based on Landsat TM data. It was necessary to form a mosaic of several satellite scenes, because Carinthia could not be covered completely by a singel scene. Nearly cloudless Landsat TM images covering all of Carinthia were available for the peroid of 1991 to 1993 (tab. 1), in which floating scene 191-27/28 coveres nearly all of Carinthia except of relatively small parts in the East and West. For preprocessing of the satellite images - geocoding and topographic normalization - a digital elevation model (DEM) was necessary. This DEM was available in a 50 m raster and was resampled to a 25 m raster.

Table 1: Satellite images.

Sensor	Scene	Acquisition date
Landsat TM	192-27 quarter	August 9, 1992
	191-27/28 floating	June 15, 1992
	191-27/28 floating	August 18, 1992
	190-27/28 quarter, flt.	June 22, 1991
	190-27/28 quarter, flt.	August 14, 1993

2.2 Ground Truth

The forest condition is mainly defined by three parameters: Forest type, stand age, and stand density. For these and some additional forest parameters ground truth derived by field work of the client was available. It was more or less equally distributed all over Carinthia. Ground truth had to undertake extensive post-processing and selection by visual control before it could be used as training set. Following selection criteria were applied:

- location within the central satellite scene
- cloud coverage
- location error due to image distortion

- location error due to mapping
- sufficient size of stand
- homogenity of area
- clear assignement to one forest class
- representativity for all classes
- variation of grey values within one class
- overlay of spectral feature space.

Finally, 299 of 583 stands from ground truth data could be used for training and verification. The training areas were more or less equally distributed all over Carinthia, but not equally distributed concerning the forest classes. This was one reason, why classification had to be performed in three independent steps, classifying each forest parameter separately. Furthermore, the ground truth data covering the smaller east and west images did not allow to classify these images indepentently from the larger central scene (compare section 6).

3 DATA PRE-PROCESSING

For mosaicking as well as for overlay of the satellite images high-precision geocoding with subpixel accuracy was essential. This was reached by using a parametric, sensor-specific mapping model taking into consideration image distortions caused by topographic relief by using a DEM. With this approach, subpixel accuracy could be reached. Furthermore, preprocessing of satellite images included atmospheric correction based on LOWTRAN7 and meteorological data as well as radiometric correction of topographic effects in each separate band. For example, the influence of relief on the signature of satellite images is described by [Schardt, 1990] for spruce and beech stands in the Black Forest, Germany. The results are shown for band TM 4 in fig. 1. Due to different

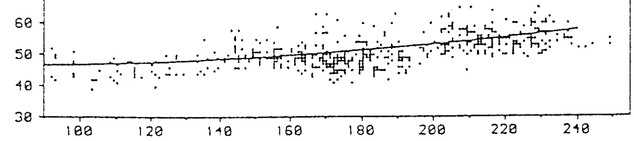

Figure 1: Signature of closed beech (+) and spruce (•) stands in Landsat TM band 4 depending on illumination [Schardt, 1990].

illumination the spectral signature of the same class changes significantly with varying slope and aspect in mountainous areas. Thus the radiometric correction is even more important for alpine regions as is characteristic for Carinthia. The topographic influence was reduced by radiometric correction using the Minneart model ([Colby, 1991]).

4 SIGNATURE ANALYSIS AND FEATURE SELECTION

In order to assess the feasibility of the task, first, results of earlier signature analyses were consulted. In general, the best suitable features for the classification of various forest parameters are well known from literature (e.g. [Coenradi, 1992, Horler & Ahern, 1986, Schardt, 1990]). The Landsat TM spectral bands TM 1 and TM 3 show a greater chlorophyll absorption, thus, the reflection is decreasing with increasing vegetation cover, whereas it is increasing in bands TM 2 and TM 4. The bands TM 5 and TM 7 are more sensitive to the biomass in general and to the leaf water content then to the green vegetation. Here the reflection also is decreasing with increasing vegetation cover. Band TM 1 is less suitable due to its sensitivity to atmospheric effects and bands TM 5 and TM 7 are strongly correlated. Therefore, the Landsat TM bands TM 2, TM 3, TM 4, and TM 5 are contain the most information for forest applications.

Besides that, the feature selection was based on further investigations such as the analysis of cluster diagramms, the calculation of correlations between features and forest parameters, and the analysis of statistical results from classification tests with diverse feature combinations, taking into consideration the most suitable phenological stages.

5 CLASSIFICATION

The classification was based on ground truth, which served as training as well as verification data sets. It had to be performed separately for each forest parameter due to underrepresentation of some classes in the ground truth data. The advantage of this approach was the selection of the most suitable feature combination for each forest parameter.

The actual edge of the forest, that is the separation of forest from non-forest areas, was classified by using a combination of thresholds in band TM 2 of the August scene (for separation of forest from other vegetation and non-vegetation) and TM 4 of the June scene (for separation from water). The forest type (4 classes from coniferous over two mixed forest classes to deciduous) were best separated in TM bands TM 3, TM 4, and TM 5 of June. The stand age (3 classes) also influenced mainly the TM bands TM 4 and TM 5, best classification results were derived by using band TM 5 and the ratio of band TM 4 and TM 3 of June. Finally, the stand density (2 classes) was classified using TM bands TM 2, TM 3, TM 4, and TM 5 of August as features.

As age of treee stand and tree speciec composition both influence the same features or spectral signatures respectively, it would be meaningful to classify these parameters jointly. Due to the unfavourable distribution of training sites within the subclasses defined by that this was not possible. For the same reason it was also impossible to take into account further factors such as the altitude or the ground cover.

5.1 Classifiers

In a broad variety of applications we acquired much experience with Maximum Likelihood [Bähr, 1985], a statistical classifier widely used in remote sensing applications. It is very important to find the best features – be that single channels or combinations – for Maximum Likelihood to yield in good performance. Therefore preprocessing is demanding both in terms of knowledge and time. On the other hand there is no necessity to care of overlearning (bad generalisation). The theoretical drawback is that Maximum Likelihood assumes the classes being normally distributed.

One Neural Network method that is a non-parametric classifier is Learning Vector Quantization (LVQ) by Kohonen [Hertz, 1991, Kohonen, 1989, Kohonen, 1995]. It looks very promising because of the efficient training process and its capability to learn non-normally distributed classes. The purpose of the training process of LVQ is to find a "codebook" which is a quantization of the training data. This codebook can be used to classify the entire image by performing a nearest neighbour labeling process.

5.2 True error rate approximation

Having no extended ground truth the performance criteria for training is true error rate approximation.

In a first step we divided all training pixels randomly into reference and testing sets. The sets are given in table 2. 10-fold cross validation was used to get approximations of the true error rates of the classifiers. A further statistical mean of estimating the performance was to carry out one design and test step to obtain the confusion matrices.

Table 2: Ground truth

	forest type	stand age	stand density
all	3145	4598	4631
reference	2661	4088	4142
test	484	510	489

5.3 Verification

Two experts from the Carinthian government and the most experienced collegue from the institute verified the results visually. This step was very important because the quality of the ground truth was not known. Furthermore, our experience with LVQ was limited at that point of time.

6 MOSAICKING

Due to the spatial distribution of the training areas all over of Carinthia a seperate training for all satellite scenes was not possible. For the scenes covering the eastern and western part of Carinthia respectively, the ground truth was not covering all classes sufficiently. Thus, first the main scene, which covers most part of Carinthia, was trained with the ground truth and classified. In order to establish a classification mosaic of all satellite scenes, the classification results of the main scene within the scene overlay were used as training areas for the classification of the edge scenes. These had to be classified separately and combined to a classification mosaic afterwards.

Table 3: Statistical results

Classification	True error rate
Forest type	$69.51\% \pm 0.78\%$
Stand age	$65.29\% \pm 0.96\%$
Stand density	$83.57\% \pm 0.65\%$

Furthermore, some small areas covered by clouds had to be replaced by classification results of cloud free scenes. Wherever possible, the edge scenes were used for this purpose. However, for some parts the central scene had to be brought in using the image not empoloyed in the original classification of the respective forest parameter.

7 RESULTS

The final approved classifications were done with Maximum Likelihood for forest type and stand age, and LVQ for stand density. While the statistical results were better for LVQ in all three classifications, the experts found problems with the LVQ results. Small classes tended to be underrepresented, the overall result was too smooth in appearance. While training with LVQ problems were encountered with repeatability of the training results with identical sample sets. Furthermore, we are suspicious that we did not obtain optimal results with LVQ. As Song and Lee [Song, 1996] point out in their very recent paper, mean problems of LVQ are:

1. good initial values for the codebook
2. no garantee for optimal codebook
3. optimal stopping point.

The CV results of the approved classifications are given in table 3, the confusion matrices in table 4.to 6. The mosaicking resulted in complete classified images where the cutting line remained invisible.

Table 4: Forest type: confusion matrix

(a)	(b)	(c)	(d)	$\Leftarrow$ classified as
77	10	12	5	(a): deciduous
31	21	20	5	(b): mixed deciduous
8	12	56	27	(c): mixed coiferous
7	9	12	172	(d): coniferous

Table 5: Stand age: confusion matrix

(a)	(b)	(c)	$\Leftarrow$ classified as
103	45	18	(a): young stands
58	183	36	(b): mature stands
11	15	41	(c): old stands

Table 6: Stand density: confusion matrix

(a)	(b)	$\Leftarrow$ classified as
54	40	(a): $0 - 60\%$
43	352	(b): $> 60\%$

8 CONCLUSION

As to chosing the best classifier it is very important to examine the confusion matrix and - additionally - to verify the results to obtain the desired outcome. This process was carried out together with the client which may not be practical in general, however, this approach was the only possibility to provide the client with adequate results due to the problems mentioned.

Neural Network classifiers do have tempting features but also unexpected drawbacks. We do not recommend to experiment with new classifiers when there is existing experience, because collecting the necessary new experience is very time consuming. Furthermore, we doubt that the results will be significantly better simply because some hidden problems with the new classifier will be overlooked easily.

As to the mosaicking, in general we would prefer to have a separate training set for each separate satellite image. In our case, the applied approach was the only possibility of composing a classification mosaic due to unsufficient ground truth in the Eastern and Western scene. The results of the overlaping area proved the approach to be successful.

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