

# CLASSIFICATION METHODS FOR 3D OBJECTS IN LASERSCANNING DATA

D. Tóvári, T. Vögtle

University of Karlsruhe, Institute of Photogrammetry and Remote Sensing, 76128 Karlsruhe, Englerstr. 7.  
[voegtle@ipf.uni-karlsruhe.de](mailto:voegtle@ipf.uni-karlsruhe.de), [tovari@ipf.uni-karlsruhe.de](mailto:tovari@ipf.uni-karlsruhe.de)

Commission VI, III/4

**KEY WORDS:** Laser scanning, Classification, Detection, Fuzzy logic, Quality

## ABSTRACT:

The object classification can play an important role in a lot of applications of airborne laserscanning data. The filtering process and the subsequent DTM generation using airborne laserscanning data can be significantly improved by classification of non-terrain objects (e.g. vegetation, buildings etc.). On the other hand classification can be also the first step of object-specific modelling, like vegetation or building reconstruction for 3D city models, design of telecommunication networks, urban planning or disaster management.

A pixel-wise classification – especially when using laserscanning data - is limited in terms of reliability of its results. Therefore, the first step of this approach will be a segmentation of 3D objects. For each segment object-specific features (e.g. height texture, shape etc.) are extracted and used for subsequent classification process. In this phase the method is based on raster data.

For segmentation a normalised DSM (nDSM) is generated by subtracting the original laser data (DSM) from a rough DTM (created by a strong filtering of the DSM). Now 3D objects can be segmented by means of specific a region growing algorithm on this nDSM. Different kind of object-oriented features are calculated for each segment, like height texture, border gradients, first/last pulse height differences, shape parameters or laser intensities. For classification two methods have been applied, on one hand a fuzzy logic classification, on the other hand a statistical method (maximum likelihood). The fuzzy logic approach resulted in an overall classification rate of about 95% for test site 'Salem' (hilly terrain) and about 90% for test site 'Karlsruhe' (flat terrain). The confusion matrix for 'Salem' show that buildings were erroneous classified as trees (5%) resp. trees as buildings (4%). The most errors can be observed at terrain objects which are confused mainly with trees (7%). Investigations concerning the statistical approach are currently done. Results and a comparison with fuzzy logic approach will be presented in this paper.

## 1. INTRODUCTION

During the last years airborne laserscanning has become one of the standard data acquisition methods in the field of surveying. Starting from the extraction of digital surface and terrain models (DSM, DTM) a great variety of applications has been developed, like creation of 3D city models, determination of tree parameters in forestry or control of power lines, e.g. in Lohr (1999). At our institute we use laserscanning data in two different projects. On one hand detection and modelling of buildings is based on these data to recognize and classify rough damages after strong earthquakes. On the other hand a high resolution terrain models including the determination of vegetation areas (position, size, density and height of trees etc.) has to be extracted from airborne laserscanning data to model hydrologic processes, e.g. runoff models to simulate floods.

For these purposes it is necessary to classify all 3D objects on the surface of the earth, i.e. mainly buildings and trees/bushes, in some cases also terrain objects like rough rocks which may be additionally included in the detected objects. Such a classification is the precondition for a class-specific modelling of buildings as well as vegetation objects. On the other hand the knowledge about the object type can be used for a significant improvement of the extraction of terrain models by a class dependent filtering of the original laser point cloud.

The first step of this approach is a segmentation of the laserscanning data for detecting 3D objects on the terrain. Inside these segments object-specific features will be extracted

which are used in the subsequent classification process. Two classification methods has been used, fuzzy logic and a stochastic approach (maximum likelihood). The influences and dependences on different feature combinations as well as a comparison of the results of different classification schemes/schemata is the main topic of these investigations.

## 2. DATA

At this state of our approach all features are derived exclusively from laserscanning data itself without additional information like spectral images or GIS data. This is caused by specific restrictions in context of disaster management - as mentioned above - where data acquisition has to be carried out also during night time and poor weather conditions. On the other hand the potential as well as the limitations of analysing airborne laserscanning data should be investigated.

For this approach data of TopoSys II sensor in raster format (grid size=1.0m) for two different test areas are used, Karlsruhe (urban environment, flat terrain, size: approx. 2km x 2km) and Salem - near Lake Constance (rural environment, hilly terrain, size: approx. 2km x 1km). Both areas were captured in first and last pulse mode while for test site Salem additionally laser intensity was registered. Figure 1 and 2 show an subset of these test sites. Salem data set was used by kindly permission of TopoSys (Germany).

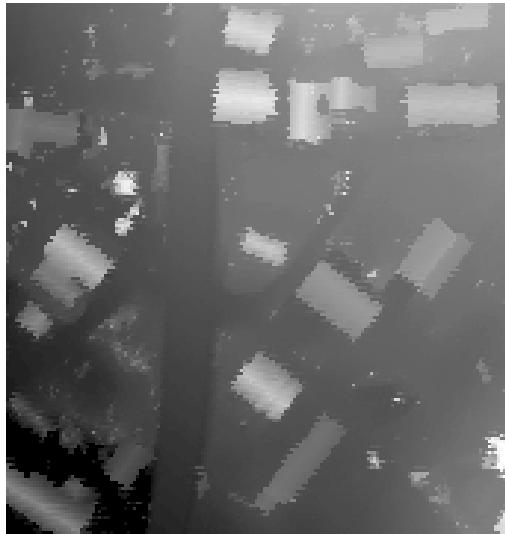


Figure 1. 'Salem' test area subset

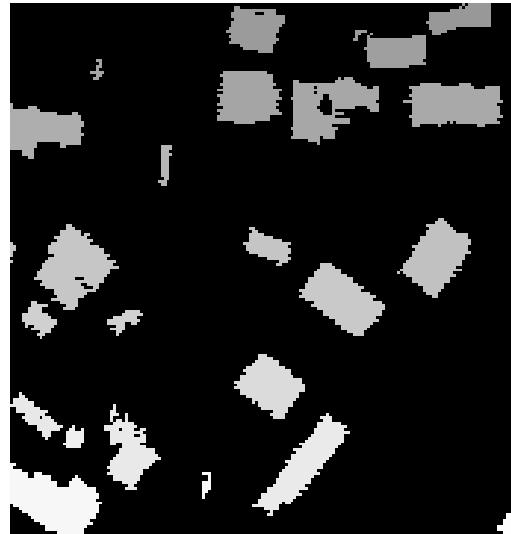


Figure 3. Segmented objects of 'Salem' test site

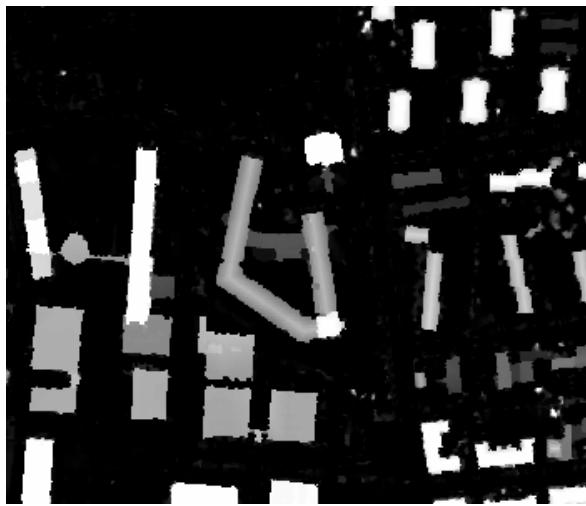


Figure 2. 'Karlsruhe' test area subset

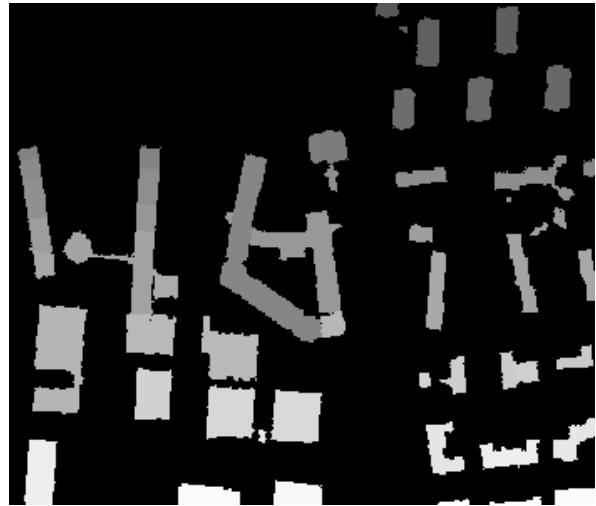


Figure 4. Segmented objects of 'Karlsruhe' test site

### 3. CLASSIFICATION OF 3D OBJECTS

#### 3.1 Definition of object classes

As mentioned above, two test sites have been investigated, Salem and Karlsruhe. In this project, the most important aspect was to investigate classification quality obtained by analysing laserscanning data with fuzzy logic methods. Therefore, the use of all main classes necessary for the applications defined above were included: *buildings*, *vegetation* and *terrain*. At test site Karlsruhe the amount of classes had to be restricted to *buildings* and *vegetation* because only one (man-made) terrain object occurs due to an extremely flat surface of the earth.

#### 3.2 Segmentation of 3D objects

Although this approach analyses raster data not the commonly used pixel based classification was preferred but an object oriented method based on the segmentation of 3D objects. Some other works in this direction can be found e.g. in (Hofmann,

Maas, Streilein, 2002; Schiewe, 2001, Lohmann, 2002). In most cases the image processing system eCognition (Definiens, 2001) is used. In opposite to these our approach is not based on general standard features but on the a-priori knowledge about the characteristic of the relevant 3D objects, i.e. about their specific appearance in laserscanning data (Voegtle, Steinle 2003).

In a first step of this approach a so-called *normalised digital surface model* (nDSM) is created to exclude the influence of topography (e.g. Schiewe 2001). For this purpose a rough filtering of the original laserscanning data (DSM) is performed to extract exclusively points on the ground (DTM). This filtering is based on our *convex concave hull* approach (von Hansen, Voegtle 1999) which results – by an accordant choose of the filter parameters – in a rough trend surface of the terrain (rough DTM) without vegetation or building points. Now the resulting nDSM is calculated by subtracting this DTM from the DSM. In this data set all 3D objects on the surface of the terrain remain, in some cases also a few terrain objects are included caused by rough rocks or sharp terrain edges. It is evident that this result hasn't to be perfect because non-relevant objects – in

this case the terrain objects – can be excluded after subsequent classification process.

Favourably, the segmentation of relevant 3D objects is carried out in such a normalised surface model (nDSM) by a special region growing algorithm which extracts and separates 3D object areas. Starting point (*crystallisation point*) is a user-defined neighbourhood of a point (e.g. N8) in this data set where all points exceed the minimal object height above ground (e.g. 2.0m). During an iterative process all new neighbouring points are included in this segment which have a height difference smaller than the maximal acceptable one (*homogeneity criterion*). This procedure results in separated areas of 3D object while very small and low objects are excluded. Fig. 3 and 4 shows the segmented objects of test site Salem and Karlsruhe.

### 3.3 Feature extraction

Inside the segmented object areas specific features for distinction of the relevant classes *buildings*, *vegetation* and *terrain* are extracted:

- Gradients on segment borders
- Height texture
- First/last pulse differences
- Shape and size
- Laser pulse intensities

The formerly tested feature *direction of normal vectors* was excluded, because of ambiguous results at smaller objects.

Significant gradients along the border of segments contribute mainly to a discrimination of buildings/vegetation on one hand and terrain objects on the other hand. While buildings and trees generally show a high amount of border gradients in laserscanning data (70% - 100%) most segmented terrain objects – even if sharp relief edges are included – have at least at some parts of the segment borders smooth transitions to the surrounding terrain model. Therefore, the amount of significant border gradients decreases below 50% in these cases.

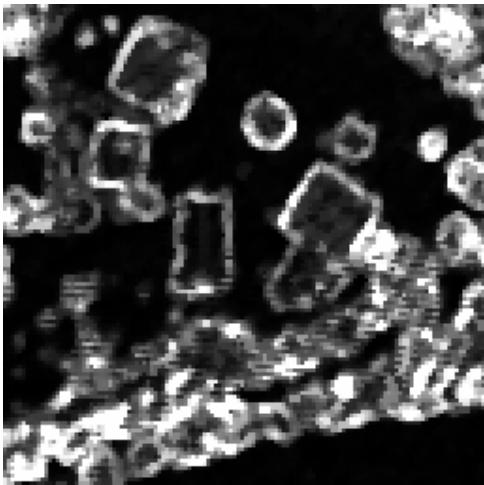


Figure 5. Grey coded height texture (Laplace operator)

In contrast height texture and first/last pulse differences allow the distinction of vegetation and buildings. Taking the shape of building roofs into account exclusively those height texture

parameters seem to be useful that model the deviations from oblique planes which fits very well to the characteristics of buildings in laserscanning data. Suitable results can be obtained by the *Laplace operator* (Maas, 1999) or by *local curvature* (Steinle, Voegtle, 2001), i.e. the difference of subsequent gradients in the four directions across a raster point. Inside the roof planes of buildings small height texture values will be obtained while vegetation objects causes significant higher values (Fig. 5.). The differences of first and last pulse measurements show a similar characteristic. Building roofs normally consist of solid material, so - dependent on the slope of the roof plane - no or only smaller differences between first and last pulse measurements can be observed. In contrast at vegetation objects with its canopy partly penetrable for laser beams larger differences will occur. Additionally, a new parameter was developed and tested, the local *variance differences* of first and last pulse measurements. But this parameter contains nearly the same information as height texture and first/last pulse differences and, therefore, was excluded for the further investigations. On principle high texture values as well as high first/last pulse differences can be observed at the border of both, buildings and vegetation. Therefore, only the interior part of the segment areas can be used for determination of these parameters to avoid disturbances by this effect.

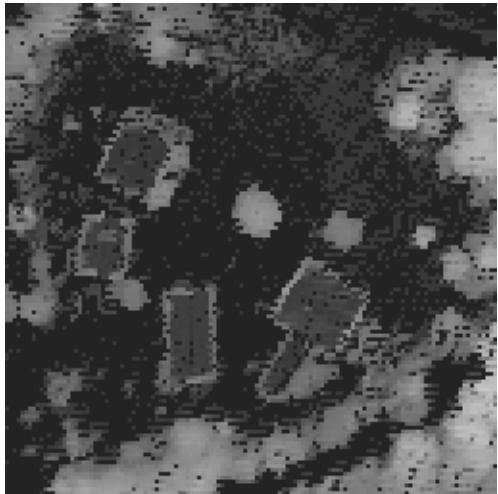


Figure 6. Grey coded first/last pulse differences

The shape of segmented object areas may contribute to the discrimination of artificial (man-made) objects (e.g. buildings, bridges etc.) and natural ones (e.g. trees, groups of trees, rough terrain or combination of both). For determination of shape parameters the contour lines of each segment has to be extracted. Because working with segments of uniform (pixel) values and clearly defined borders a simple edge tracking algorithm can be applied to provide the 2D contour lines. After smoothing these lines, e.g. by the well-known Douglas-Peucker method (Douglas & Peucker 1973), shape and size of these polygons can be analysed. Former investigations have shown that commonly used standard parameters like *roundness*, *compactness* etc. don't fulfil the requirements which are necessary to distinguish between the object shapes in this application. Therefore, alternative parameters had been developed like *geometry of the n longest lines*, where at first the *n* longest lines of a contour polygon are selected (e.g. *n*=4). These lines are analysed in terms of parallelism and orthogonality. A measure is calculated which is 100 for perfect

parallel or orthogonal lines and decreases proportional to increasing deviations from that. This shape parameter has proved to be suitable to distinguish artificial and natural objects in most cases, if their area is large enough. Small object sizes lead to ambiguities. Fig. 7 and 8 show examples of filtered contour polygons of typical building and vegetation objects respectively.

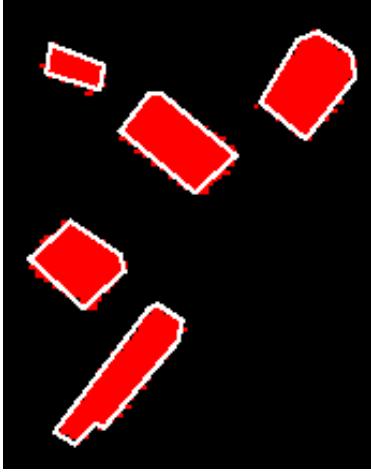


Figure 7. Contour polygons of typical building segments

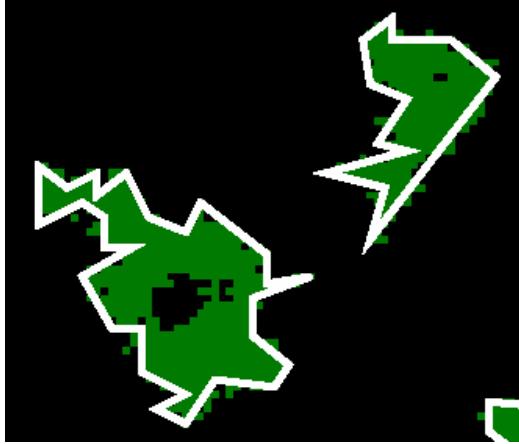


Figure 8. Contour polygons of typical vegetation segments

For one test site (Salem) laser intensities were available which are recorded by the new TopoSys II sensor. This additional information was also included in the test program. The intensity of laser pulses depends highly on the characteristic of the reflecting material. In most cases buildings with commonly used roof tiles cause much higher or in the other case nearly the same intensity values than vegetation. An example of typical intensity characteristics of buildings and vegetation can be seen in Fig. 9. Some statistical values like minimum, maximum, average and RMS was determined for all features mentioned above. In every case the average value was selected for classification purposes as it has proved to be the most suitable one.

### 3.4 Fuzzy classification

The subsequent classification and its results depend on the preceding segmentation process because only segmented objects

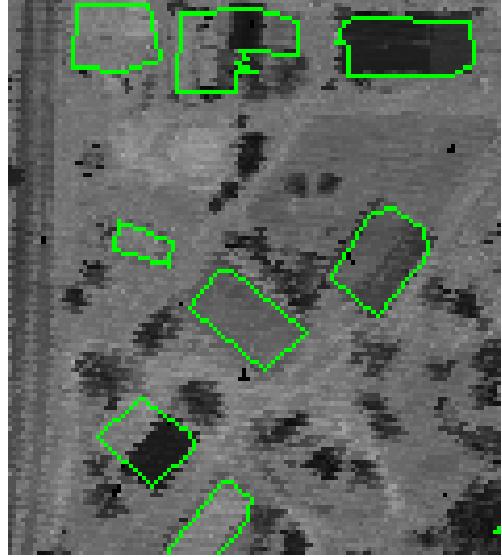


Figure 9. Laser pulse intensities with extracted building boundaries

are classified. The *fuzzy logic* classification is based on the extracted features which have been described above. Fuzzy logic presents an opportunity to get answers to questions with a truth value in a range of 0 and 1. Fuzzy logic has been used in a wide range of applications, mainly in system controlling, and supports classification processes as well. The uncertain and often contradictory information can be handled and quite accurate results may be obtained. The fuzzy theory tries to blur the boundary between membership and non-membership. Therefore the elements can be members, non-members and partially members as well. The basic idea is to model this uncertainty of classification parameters (features) by so called *membership functions*. A user has to define such a membership function for every parameter and every class (fuzzification). They may be built up by straight line sections in order to make computation easier, but also functions of higher degree can be defined dependent on the respective application. But in practice it has been proved that different approach don't effect the results too much. Normally, membership functions are defined in an empirical way by means of training samples visually selected and interpreted by an operator. In this case about 25 segments have been chosen for each class. Histogram analysis may help to determine the parameters of membership functions, but a control and – if necessary – an improvement of these functions should be done in every case. These membership functions have proved to be quite stable and robust independent on different locations (Voegtle, Steinle 2003).

A concrete value of feature  $i$  leads – by means of the corresponding membership function – to the related degree of membership  $\mu_{ij}$  for every class  $j$ , in this project  $j=3$  (buildings/vegetation/terrain). All membership values for the same class  $j$  have to be combined for a final decision (inference process). The original Zadeh-type operators are used, such as minimum, maximum and product, besides this a weighted sum was tested also. The minimum, maximum and product operator for a class can be defined as:

$$\begin{aligned}\mu_{(A \wedge B \wedge C)}(x) &= \min(\mu_A(x), \mu_B(x), \mu_C(x)) \\ \mu_{(A \vee B \vee C)}(x) &= \max(\mu_A(x), \mu_B(x), \mu_C(x)), \\ \mu_{(ABC)}(x) &= \mu_A(x) * \mu_B(x) * \mu_C(x),\end{aligned}$$

where  $A, B, C$  = extracted features

$\mu_A, \mu_B, \mu_C$  = degree of membership of the features

For the minimum operator the truth value of the result is defined by the minimum truth value of the used features which is the logical AND implementation in fuzzy environment. Similarly, the maximum truth value of all used features determine the truth value of a class by the maximum operator. This operator is used in fuzzy as logical OR. For these two operators, the fuzzy sets of the classes should constitute complementary membership functions, so the sum of the degrees of membership for every feature value should be 1. Therefore, the elements are classified into non-correlated classes and all features are taken into consideration with the same importance. In cases where the sum of the degrees of membership is more than 1, the accordant feature plays a more important role in the calculation. Using the product operator this is of lower importance, since only the differences between the truth values of the classes for a feature cause differences in the final result. For calculation of a weighted sum, an individual weight is assigned to each feature. This weight may be constant to express the reliability of a certain feature in general, but also variable depending on another feature. For example, the shape parameter *geometry of n longest lines* expresses the parallelism and orthogonality of these lines. However, the reliability of this feature depends on the size of the object. It can be observed that this feature provides more reliable values if larger segments are concerned while at smaller segments only short contour lines can be extracted which leads – due to noise and rastering effects – to increasing deviations from parallelism and orthogonality.

The inference procedure results in a crisp value for each segment and class. In every case the final decision is based on the maximum method, i.e. the class of highest probability will be assigned to the corresponding segment. As an example the confusion matrix for the product operator in shown in Table 1. In Table 2 the results obtained by different inference operators are assembled for both test sites. It is obvious that the results are not independent on the respective operator. Using a combination of all available features the minimum and particularly the maximum operator provide results of lower classification rates. For test site Salem this tendency is more significant than for Karlsruhe. Product and weighted sum method achieve higher classification rates of similar dimension. Other combinations where not all features were included lead to increasing differences.

Product	Buildings	Vegetation	Terrain
Buildings	95	5	0
Vegetation	4	96	0
Terrain	0	7	93

Table 1. Confusion matrix for the product operator (Salem)

Operator	Karlsruhe	Salem
Product	90	95
Weighted sum	90	94
Minimum	88	64
Maximum	87	74

Table 2. Classification results by different operators in fuzzy logic

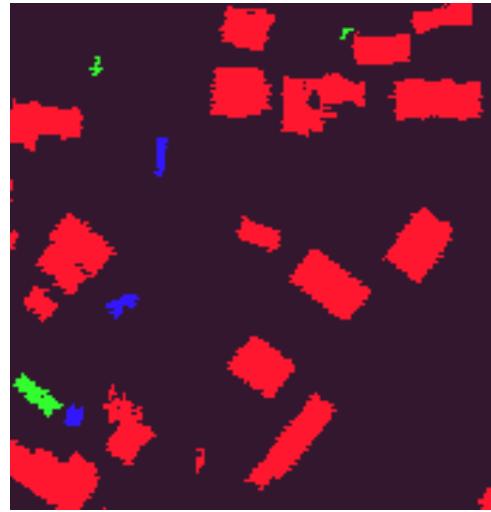


Figure 10. Classified segments (red- building, blue- terrain, green- vegetation)

Border gradients	Height texture	Fp/lp differences	Shape	Laser pulse intensities	Class. rate buildings	Class. rate vegetation	Class. rate terrain	Overall class. rate
+	+	+	+	+	95	96	93	95
+		+	+	+	93	96	80	92
+	+		+	+	84	79	87	84
+	+	+		+	96	88	93	94
+			+	+	85	67	73	80
	+	+	+	+	93	96	80	92
		+	+	+	83	96	93	87
+	+	+	+		89	79	93	88
+	+	+			93	38	93	81

Table 3. Feature combinations for test area Salem

Border gradients	Height texture	Fp/lp differences	Shape	Class. rate buildings	Class. rate vegetation	Overall class. rate
+	+	+	+	89	90	90
+		+	+	93	85	89
+	+		+	86	80	83
+	+	+		88	86	87
+			+	91	62	78
		+	+	90	89	90

Table 4. Feature combinations for test area Karlsruhe

Due to this quality assessment of different inference operators *product* has been selected as standard operator for subsequent investigations. To compare the reliability of the defined features and to demonstrate the influence of each of them 9 different feature combinations have been calculated and the influence of missing features has been observed, whereas the independence of the features was assumed. These feature combinations and their results can be seen in Table 3 and 4. Besides the individual class-related values also an overall classification rate has been included. The results show that the amount of significant border

gradients which should separate terrain objects has evidently no influence on the results in test site Karlsruhe. Comparing first/last pulse differences and height texture which both contribute to discriminate buildings and vegetation, it is obvious that height texture is of less importance because the averaged improvement of classification rate is only about 1% to 3%. For first/last pulse differences this value is about 7% to 10%. Adding the shape parameter to the feature combination only at test site Karlsruhe a slight improvement of the results (about 2%) can be observed due to the higher amount of larger buildings compared to rural region of Salem. The intensity values – only available for test site Salem – contribute significantly to the classification success. An increase of about 7% was achieved.

### 3.5 Maximum-likelihood classification

Besides the fuzzy logic approach with different inference operators also a statistical classification method has been applied to be able to compare the fuzzy logic results with a well proven standard approach and to discuss the differences. A maximum likelihood classification was chosen for this purpose. To obtain reasonable results exactly the same training and control objects has been used in this classification.

The results for both test sites Karlsruhe and Salem – based on the combination of all parameters - are assembled in Table 5. For reasons of comparison also the main classification rates of fuzzy logic are included in this table.

	Test site	Class. rate buildings	Class. rate vegetation	Class. rate terrain	Overall class. rate
Fuzzy logic	Salem	95	96	93	95
	Karlsruhe	89	90	-	90
Max.-lik.	Salem	96	96	93	95
	Karlsruhe	92	86	-	89

Tab. 5 Comparison of main classification rates between fuzzy logic and maximum-likelihood method

It is obvious that classification rate of vegetation in test site Karlsruhe is higher for fuzzy logic than for maximum likelihood but contrary for building while the total classification rate is the same. These differences are caused by the influence of the definition of membership functions in the fuzzy logic approach. Even a modification of the related membership functions in order to increase the classification rate of buildings would inevitably lead to an accordant decrease of classification rate for vegetation, so the resulting overall classification rate would remain nearly the same. The results of both methods are in the same dimension if all available features are used. If combinations of only a few features are applied no definite assessment can be made. For test site Karlsruhe fuzzy logic seems to provide better results while it is a contrary situation for Salem. The advantage of fuzzy logic may be that the transferability to other locations seems to be easier especially for applications where only a few training areas/objects are available due to its robust membership functions.

## 4. CONCLUSION

Using a priori knowledge about the characteristics of 3D objects in laserscanning data for definition and extraction of object-

relevant features suitable results can be achieved using fuzzy logic or maximum likelihood classification. An improvement may be possible by introducing a hierarchical classification scheme based on a set of rules. Such a logical decision structure will be implemented in the next phase of this project to overcome some disadvantages of standard inference operators like they were used in these investigations. Additionally a post-segmentation has to be integrated in this approach to separate different object types which are erroneously combined to one segment, e.g. vegetation objects which are located directly beside a building.

## REFERENCES

- Definiens, 2001. [www.definiens.de](http://www.definiens.de)
- Douglas, D., Peucker, T., 1973. Algorithms for the reduction of the number of points required for represent a digitized line or its caricature. *Canadian Cartographer*, 10(2), pp. 112-122.
- von Hansen, W. & Voegtle, T., 1999. Extraktion der Geländeoberfläche aus flugzeuggetragenen Laserscanner-Aufnahmen. *PFG*, Nr. 4/1999, pp. 229-236.
- Hofmann, A. D., Maas, H.-G., Streilein, A., 2002 Knowledge-Based Building Detection Based on Laser Scanner Data and Topographic Map Information. *ISPRS Comission III, Vol.34, Part 3A "Photogrammetric Computer Vision"*, Graz, Austria, A169-174
- Lohmann, P.: Segmentation and Filtering of Laser Scanner Digital Surface Models, *Proc. of ISPRS Commission II Symposium on Integrated Systems for Spatial Data Production, Custodian and Decision Support, IAPRS*, Volume XXXIV, Part 2, pp. 311-315, Xi'an, Aug. 22-23, 2002
- Lohr, U., 1999. High resolution laser scanning, not only for 3D-city models. *Fritsch, D. and Spiller, R.: Photogrammetric Week '99*, Wichmann, Karlsruhe, Germany
- Maas, H.-G., 1999. The potential of height texture measures for the segmentation of airborne laserscanner data. In: *Fourth International Airborne Remote Sensing Conference and Exhibition / 21st Canadian Symposium on Remote Sensing*, Ottawa, Ontario, Canada.
- Schiwe, J., 2001. Ein regionen-basiertes Verfahren zur Extraktion der Geländeoberfläche aus Digitalen Oberflächen-Modellen. *PFG*, Nr. 2/2001, pp. 81-90.
- Steinle, E. & Voegtle, T., 2001. Automated extraction and reconstruction of buildings in laserscanning data for disaster management. In: *Automatic Extraction of Man-Made Objects from Aerial and Space Images (III)*, E. Baltzavias et al. (eds.), Swets & Zeitlinger, Lisse, The Netherlands, pp. 309-318.
- Tilli, T. 1993. *Mustererkennung mit Fuzzy-Logik*. Franzis-Verlag GmbH, München
- Voegtle, T., Steinle, E., 2003. On the quality of obeject classification and automated building modelling based on laserscanning data. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Dresden, Germany Vol. XXXIV, Part 3/W13, 8-10 October 2003, ISSN 1682-1750