

OBJECT CLASSIFICATION IN LASERSCANNING DATA

D. Tóvári, T. Vögtle

University of Karlsruhe, Institute of Photogrammetry and Remote Sensing, 76128 Karlsruhe, Englerstr. 7.,
tovari@ipf.uni-karlsruhe.de, voegtle@ipf.uni-karlsruhe.de

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ABSTRACT:

Airborne laserscanning become a common surveying tool in the last years. A lot of applications are based on digital terrain models in urban planning, forestry, topographic mapping, environmental monitoring or disaster management. 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.).

For this reason it is very important to classify the objects on the surface of the earth. The commonly used pixel-wise image classification methods are limited in terms of reliability of its results, especially when using laserscanning data. Therefore, a segment based classification method has been developed. The segments can be buildings, building parts, connected vegetation, or parts of it. This kind of segment based classification can be the premise of 3D object reconstruction. In the first step of object segmentation, a normalized digital surface model (nDSM) is generated by extracting ground points exclusively. The full automated DTM generation can not result a perfect DTM, some kind of sharp terrain edges and their surrounding areas can be filtered out as well. Besides the man-made objects and vegetation, this nDSM also contains some terrain parts. After classification, these terrain objects can be reintegrated to the data of the terrain model, and a new one can be generated in higher quality.

After segmentation, different kind of object-oriented features are calculated for each segment, like height texture, first/last pulse differences, etc. A fuzzy logic approach is used to obtain a reliable building, vegetation and terrain classification based on these features. This classification is based on segment objects, so not segmented objects can't be classified. The segmentation is based on the last pulse laser data in order to avoid mixed segments (e.g. building with trees). On the other hand, as a disadvantage, not all vegetation objects are segmented, since the last pulse data set contain buildings, and partly vegetation. Therefore, a great amount of vegetation can't be classified. To solve the problem, a hierarchical approach of segmentation and classification has been developed. Buildings are classified from the last pulse data, than –after masking building objects- vegetation from first/last pulse data.

1. INTRODUCTION

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. 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 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 our approach is based on a classification of 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 applied, fuzzy logic and a stochastic approach (maximum likelihood). Investigations show

that suitable results can be achieved by these methods (Tóvári, Vögtle, 2004). An improvement of classification process for better vegetation detection are presented in this paper.

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 analyzing airborne laserscanning data should be investigated.

For this approach data of TopoSys II sensor in raster format (grid size=1.0m) has been used from different test sites, e.g. 'Salem' near Lake Constance (rural environment, hilly terrain, size: approx. 2km x 1km) which was captured in first and last pulse mode, additionally laser intensity was registered. Figure 1 shows a hill shaded subset of this test site. The data set was used by kindly permission of TopoSys (Germany).

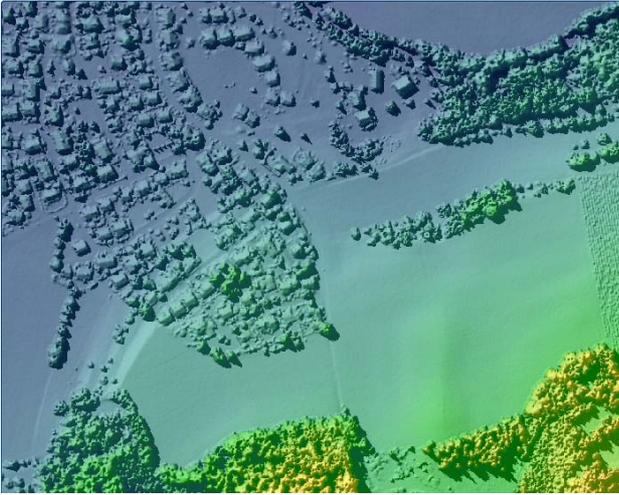


Figure 1. Hill shaded 'Salem' test area subset

3. CLASSIFICATION OF 3D OBJECTS

3.1 Definition of object classes

In this project, the most important aspect was to develop a classification process for analysing laserscanning data with fuzzy logic method. Therefore, all main classes – necessary for the applications defined above – were included: *buildings*, *vegetation* and *terrain*.

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. In this context some other works can be found (e.g. Hofmann, Maas, Streilein, 2002; Schiewe, 2001). In these cases the image processing system eCognition (Definiens, 2001) is used. In opposite, our approach is not based on general standard features but on the a-priori knowledge about the characteristic of 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 specific 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 a threshold (*homogeneity criterion*). This procedure results in separated areas of 3D objects while very small and low objects are excluded.

3.3 Feature extraction

Inside each segmented object area 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

Significant gradients along the border of segmented 3D objects 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 most cases.

In contrast height texture and first/last pulse differences allow the distinction of vegetation and buildings. Taking the common 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* (e.g. Maas, 1999) or by *local curvature* (e.g. 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 cause significant higher values. 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. 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.

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. 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*: after selection of the *n* longest lines of a contour polygon (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, i.e. if the area of the corresponding segment is large enough. Small object sizes lead to ambiguities. Figure 2 shows some examples of contour polygons of typical building and vegetation objects respectively.

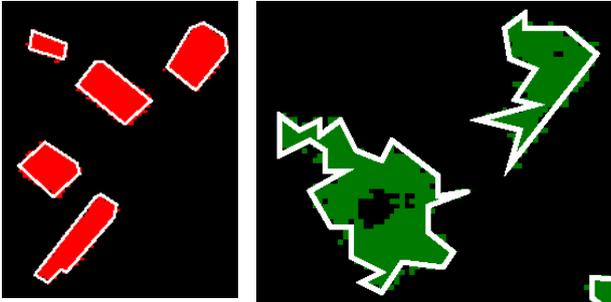


Figure 2. Contour polygons of typical building (left) and vegetation segments (right)

Laser intensities were also available which are recorded by the new TopoSys II sensor. This additional information was also included in our test program. The registered intensity of laser pulses depends highly on the characteristic of the reflecting surface element (material, geometry etc). In most cases buildings with commonly used roof tiles cause very high or – in the other case – nearly the same intensity values as vegetation. 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 *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. Uncertain and – in some cases – 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 approaches don't influence 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.

A concrete value of feature i leads – by means of the corresponding membership function – to the related degree of membership $\mu_{i,j}$ 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). According to former investigations the *product operator* seems to be the most appropriate one.

The inference procedure results in a crisp value for each segment and class. In every case the final decision is based on the class of highest probability which will be assigned to the corresponding segment. As an example for the obtained classification results the confusion matrix for *product operator* is shown in Table 1.

Product-Op.	Buildings	Vegetation	Terrain
Buildings	95	5	0
Vegetation	4	96	0
Terrain	0	7	93

Table 1. Confusion matrix of classification rates [%] for the product operator

3.5 Maximum-likelihood classification

Besides the fuzzy logic approach a statistical classification method has been applied in order to compare the results of fuzzy logic with a well proven standard approach. A maximum likelihood classification was chosen for this purpose.

This comparison of classification methods show almost the same overall classification rates, however, the classification rates for buildings are slightly better for maximum-likelihood and vice versa for vegetation. These differences are caused by the influence of the determination of fuzzy membership functions by a human operator.

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. VEGETATION DETECTION AND SEGMENTATION

As mentioned above, not all vegetation objects can be segmented and classified if last pulse data are used. In many cases the vegetation is not dense enough, therefore, the laser pulse is reflected partly on the ground. In these cases, the trees don't appear in the last pulse DSM/nDSM, even if the first/last pulse differences are much higher than inside building objects. However, building edges cause a similar effect, but it leads only to thin, linear appearances in the difference data set while vegetation objects cause larger difference areas. Since the buildings are already classified, it is possible to mask out these building edges from the height difference data.

Now these data can be used for a second segmentation and classification procedure of the still missing vegetation objects. Figure 3 shows the result of this hierarchical classification process.

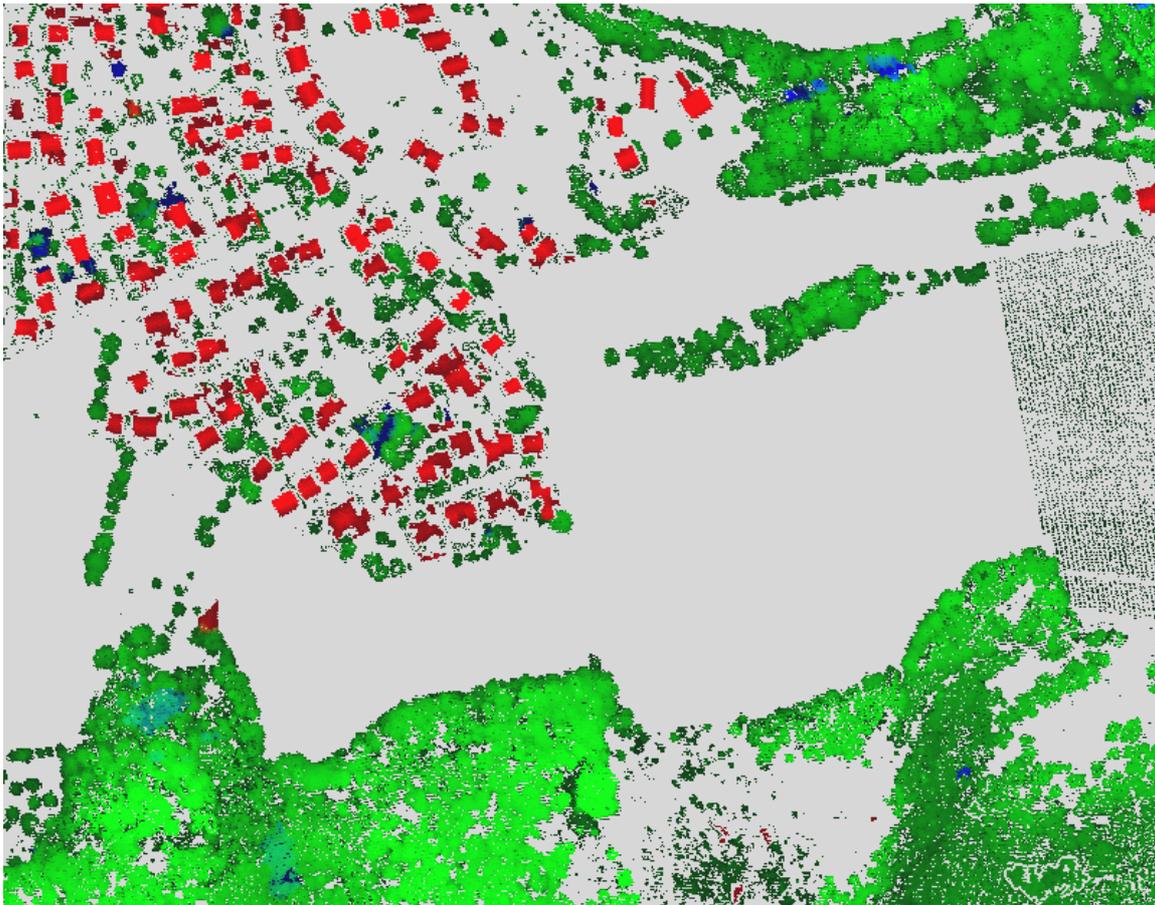


Figure 3. Classification results of hierarchical fuzzy logic approach (red - buildings, green – vegetation, blue – terrain)

5. DTM QUALITY IMPROVEMENT

DTM quality can be improved now by means of the knowledge obtained by the hierarchical classification process. Resulting building and vegetation areas can be directly masked out of the original DSM while classified terrain objects may remain in this data set. To avoid some remaining errors, e.g. artefacts at the border of excluded building or vegetation objects, a filtering procedure – in this case our convex concave hull approach – has to be carried out. The advantage of the presented method is that this filtering procedure can be controlled and adapted by the previously obtained classification results, e.g. different filter parameters can be applied to building, vegetation and terrain areas. Therefore, high quality DTM can be generated with this approach.

6. CONCLUSION

Classification of 3D objects in laserscanning data has proved to be very suitable for different applications, i.e. as precondition for an object related 3D modelling of buildings and trees as well as a significant improvement of DTM generation. For this purpose specific object oriented features – representing the characteristics of the defined object classes in airborne laserscanning data – are extracted from these data exclusively. A subsequent hierarchical classification process – fuzzy logic as well as maximum likelihood – based on these features can provide suitable results (> 92% overall classification rate). Further improvements may be obtained by an additional subsegmentation in the highest hierarchical level because in some

cases two different objects may be merged into one segment, e.g. a tree located directly beside a building. In this context the whole segmentation – at the moment divided into two hierarchical steps – may be developed to one unique approach taking simultaneously geometrical as well as laser specific properties (e.g. first/last pulse differences) into account.

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