

OBJECT-BASED ANALYSIS OF AIRBORNE LASER SCANNING DATA FOR NATURAL HAZARD PURPOSES USING OPEN SOURCE COMPONENTS

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KEY WORDS: Natural Hazard Management, Airborne Laser Scanning, Open Source GIS, Segmentation, Classification

ABSTRACT:

Geoinformation is an important basis for planning strategies, natural hazard modelling, process detection, and risk analysis. Airborne Laser Scanning is an operational working method for area wide data acquisition and provides 3D information in a high spatial resolution. The data contains detailed information to characterise surface properties which is, however, not obvious to extract from the massive cloud of points or elevation raster. Object-based analysis allow to obtain additional information for surface classification.

The following paper presents the current status of work for determining surface properties and object classification. The workflow for object-based analysis of Airborne Laser Scanning data is integrated in the Open Source GRASS GIS environment using the implemented image processing and standard GIS functionalities. Two examples show the classification of "raised" objects and the detection of geomorphologic structures in Airborne Laser Scanning elevation data.

1. INTRODUCTION

1.1 Motivation

Many applications in the field of natural hazard management require topographical data as input for modelling which can be provided by Airborne Laser Scanning (ALS). While for risk zone mapping and damage estimations the detection of man-made objects is required, geomorphologic structures and morphometric parameters can be used to identify and monitor processes like erosion or slope movements (Kääb et al., 2005; Hübl et al., 2002). ALS data is characterized by high spatial resolution which leads to a huge data volume making the data handling difficult. Furthermore most applications can not handle the original ALS point cloud, but require derived and classified data as model input. This paper shows the extended concept of an object-based classification and analysis approach which was introduced by Rutzinger et. al (2006). The aim is the construction of a classification workflow for ALS data and its derivatives using the advantage of object-based classification, e.g. object related feature calculation, object topology, and acceptance of different data models.

1.2 Related Work

Land cover classification of ALS data is studied for some time already. Sithole (2005) presents segmentation and classification algorithms for micro (local surface roughness) and macro (predominant landscape objects) object detection in 3D ALS data. Man-made and natural objects are distinguished in sense of buildings, bridges, vegetation, and bare earth.

Another approach for segmenting ALS data using texture measurements and mathematical morphological filtering is presented by Oude Elberink and Maas (2000). Information on first pulse/last pulse difference, texture, reflectance and the

calculation of a normalized Digital Surface Model (nDSM) are the input for separating man-made objects and natural objects into further subclasses with a k-means classification.

It shall be noted that Sithole works in the point cloud directly, whereas Oude Elberink and Maas perform the classification in the raster domain. Other algorithms for segmentation of the point cloud are given in Vosselman et al. (2004) and Filin and Pfeifer (2006) and the references therein.

The usage of ALS for analysing geomorphologic structures is still at the beginning. That ALS provides objective information for the detection of geomorphologic structures is shown by McKean and Roering (2004) distinguishing between three different active units of a landslide by deriving surface roughness parameters from a ALS Digital Surface Model (DSM). Glenn et al. (2006) use ALS data to analyse the relationship between surface morphology, landslide activity and material type.

The workflow for object-based image analysis which is implemented in the software eCognition is designed for 2D and 2,5D data analysis respectively (Benz et al., 2004). A region growing segmentation algorithm building up a hierarchical object representation is combined with a fuzzy classification rule base. An example for classification of ALS elevation data to derive buildings, high vegetation and bare earth with this approach is shown by Tóvári and Vögtle (2004). Asselen and Seijmonsbergen (2006) segment a slope map derived from ALS data to classify geomorphologic structures with mean slope and absolute elevation as object features.

2. METHOD

2.1 ALS data and derivatives

The raw data collected by ALS is a 3D point cloud with information on spatial location (X,Y,Z) and an intensity value

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(I) for each echo. Depending on the sensor it is possible to record multiple echoes. The used data for these investigations was recorded by an Optech ALTM 2050 sensor which records the first and the last echo (or pulse) of every laser shot.

Primary derivatives of the original ALS point cloud are points classified into bare earth and off-terrain points, which are further interpolated to Digital Surface Models (DSMs) and Digital Terrain Models (DTMs) (Wehr and Lohr, 1999). Furthermore a first/last pulse difference model (FLDM) can be calculated, i.e. elevation of first reflection subtracted by elevation of last reflection.

The quality of object representation depends strongly on point density, scan geometry and surface type. The representation of vegetation depends additionally on the flying season (Wagner et al., 2004).

2.2 Open Source Components

The workflow presented here is set up on a LINUX platform using GRASS GIS as environment for the implementation of new modules. GRASS GIS is designed for both Graphical User Interface (GUI) and command line use. The built-in commands can be batched together with LINUX programs using UNIX-shell scripting as an interface, which gives broad possibilities on adaptation of the existing GIS functionalities (Neteler and Mitasova, 2004). Furthermore new modules are added as python scripts into the workflow (Python Software Foundation, 2006).

The object-based analysis workflow is connected to the Information System LISA (LIDAR Surface Analysis) which provides functionalities on ALS point cloud storage, management and analysis (Höfle et al., 2006).

2.3 Concept of an object-based workflow for ALS data analysis

The main objective of the designed workflow (Figure 1) is the integration of different data models to enable iterative object-based analysis. The combination of the analysing steps a) segmentation, b) object feature calculation, c) classification, and d) error assessment already allows the integration of object-based information in the classification step as shown by Rutzinger et al. (2006). The extension of the workflow towards different input types, iterative analysis and consideration of spatial object topology offers further analysis possibilities.

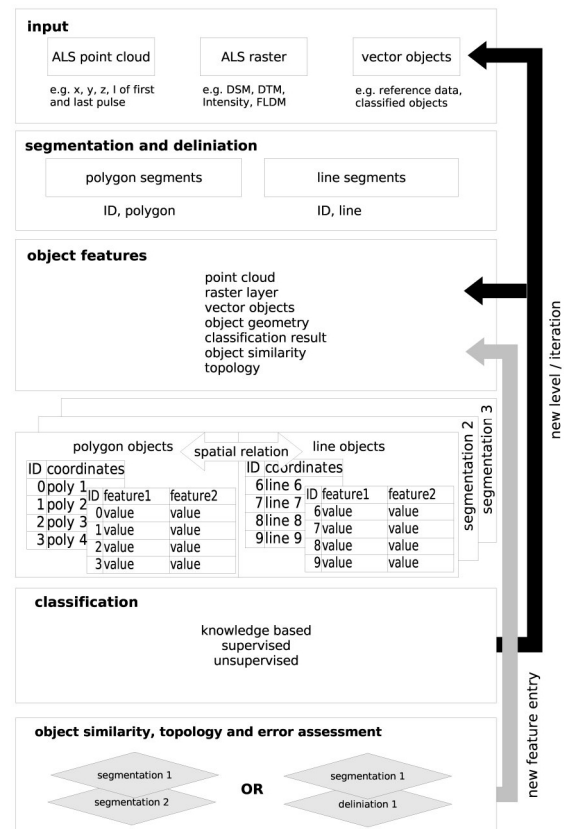


Figure 1. Object-based classification workflow for ALS data

At the current stage raster data, line and polygon vectors can be handled as **input data** sets. The segments derived from raster input data can be either polygon segments or line segments (e.g. in case of geomorphologic structures, see section 3.2).

The **object features** are either derived directly from the input data source, from the segments itself (e.g. object geometry) or from spatial object relations. In the case of line segments features can be calculated either on the spatial surrounding, defined by voronoi diagrams of polygons (Mayya and Rajan, 1994), or on the line itself.

The spatial relationship is on the one hand applied to neighbours within the same layer or on the other hand between two different layers (see error assessment). Spatial neighbours within the same layer (Figure 2a) are either selected by the number of neighbours or by the distance to the object of interest. The centre of an object is calculated by adding all coordinates defining an object and dividing them by the amount of vertices (vertex centre of gravity). The distance measurements from object to neighbours are: b) centre-to-centre where a Delaunay triangulation of the centre points can be used to determine, if two objects are neighbours and the edge length determines the distance between two neighbours, c) vertices-to-centre using average, minimum, maximum, etc. as distance measurement between two objects, or by d) voronoi diagrams of polygons where two objects are neighbours, if their voronoi regions are adjacent. Depending on the distance measurement the order of the nearest neighbours differs. The situation in Figure 2 shows that using triangulation neighbour 2 is nearest while using distances of c) or d) neighbour 3 is nearest to the object of interest.

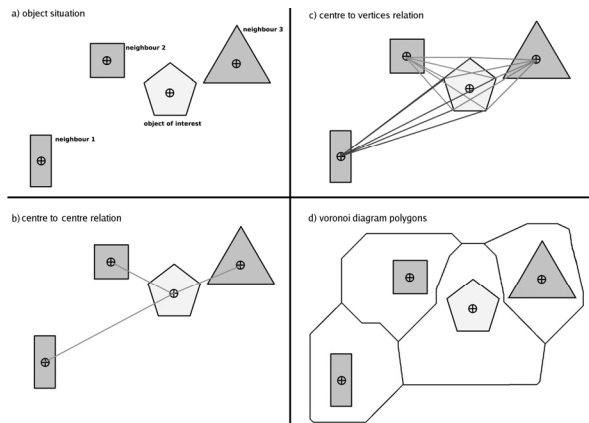


Figure 2. Definition of spatial neighbours

The objects are assigned to their corresponding class by a rule-based **classification** tree. The features are weighted by the user which implies knowledge about the objects and their representation within the feature space. The specified weights for each feature layer show the quality of the object description. In the **error assessment** step classified and reference objects are compared on object level. Comparisons at the pixel level have the disadvantage that a) inhomogeneities in coordinate systems, and b) different representation of objects (e.g. roof outline vs. wall at ground level) have influence on the judgement of the method. While comparison can be done at pixel level (Rutzinger et al., 2006) an object-based comparison is shown here. In object-based error assessment the spatial distribution of the objects is investigated. This is done by the selection of reference polygons by derived centres of the classification data set. If the central point of a classified object lies within a reference object and vice versa, it is handled as right classified. Based on the number of spatial correct detected objects, the percentage of correct classified objects can be calculated.

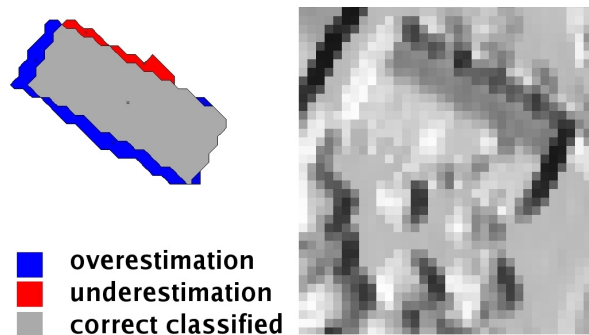


Figure 3. Error assessment

Furthermore the accuracy of the classification on object level is done by comparing the percentage of over- or underestimated and the overlapping areas. Figure 3 shows a building object with a successful spatial check with over- and underestimated areas. This information on object similarity is also used to compare two different segmentations for example to investigate object changes in multi-temporal data (Blaschke, 2005). The information on object similarity is stored as a feature entry and then used for a second iteration on object classification.

Likewise, the similarity of the features computed for an object as obtained by different methods can be computed. The feature is in this case computed from one data source alone, e.g. elevation raster, but for the different areas (outlines) from the two segmentation method.

2.4 Object representation in ALS data

The differentiation of classes depends on the final application. In the sense of a land cover classification a site can contain man-made and natural objects, while in the terminology of ALS point cloud filtering for DTM generation the primary differentiation is about bare earth and raised objects. While points classified as bare earth contain roads and open land, the class raised objects contains high vegetation and buildings for example as well.

In the following examples a target class out of the spectrum of land cover classification is defined first. This requires individual segmentation approaches in a defined scale interval, adapted features and classification rules to reach a suited object description.

3. RESULTS

3.1 Example 1: urban environment - building detection

The test site for high object detection in an urban environment focusing on buildings and high vegetation is the city of Hohenems in Vorarlberg/Austria.

A common problem on building classification in urban areas is the differentiation between buildings and directly connected trees (Rottensteiner et al., 2005). Therefore a high-vegetation mask is derived from the FLDM first.

Vegetation mask: The FLDM contains parts of building edges, masts and power lines, erection cranes and high vegetation. Filtering all pixels with first/last pulse difference with a four pixel neighbourhood low pass filter and the removal of small areas considered as noise by an area criterion produces a high-vegetation layer. This layer is used as a mask for further building detection.

Segmentation: The segments for building detection are derived by a fill sinks approach (Arge et al., 2001) applied on the inverted DSM. The segments of high objects are defined by a threshold of 3.0 m. The separation between building segments and high vegetation segments is done by exploiting the derived vegetation mask.

Feature calculation: The significant features for the description of building objects are the standard deviation of height, the average of the first/last pulse difference, object shape (perimeter per area), and object area.

Classification rules: The calculated features are the input in the classification step. The best results for building classification are achieved by choosing first/last pulse difference between 0.5 m and 3 m, standard deviation of height from 0.04 m to 4.09 m, shape index smaller than 0.6 m^{-1} and an area larger than 100 m^2 .

Error Assessment: The comparison of the classified buildings (Figure 4) with the digital cadastral map assuming spatial overlaying objects (based on object centres) as right classified (see section 2.3) leads to a producer's accuracy (PA) of about 91% and a user's accuracy (UA) of about 93%. Looking to the result on object level the average building object reaches 78% PA and 73% UA.



Figure 4. Classified buildings Test site Hohenems, Austria

3.2 Example 2: geomorphologic structures

Wall structures on bare earth indicate geomorphologically interesting areas like torrent erosion, scarp of landslides or moraines and rock glaciers. These landscape objects are characterized by linear occurrence. Therefore the introduction of linear object primitives is reasonable. The implementation of line segments and the calculation of features is still on an experimental level. The following settings are tested at a test site in the Austrian Alps/Tyrol. The test site contains moraine complexes and rockglaciers (Kerschner, 1993).

Segmentation: Input for the segmentation is a maximum curvature raster from the ALS DSM processed by a 15x15 meter calculation window. The calculation window must be applied to the approximately width of the object of interest. If the window does not fit in size, only sub- and superior structures respectively are mapped. A threshold of 0.05 m^{-1} is applied for the detection of ridges and -0.05 m^{-1} threshold for the lower edges of ridges. These areas are thinned by a mathematical morphologic filter to finally extract the line vectors.

Feature calculation: This kind of object primitives leads to constrictions in the step of feature calculation especially for features derived from ALS data directly. With the calculation of the voronoi diagram polygons for the line segments it is possible to calculate the features based on this topological neighbourhood area. Figure 5 shows line objects for wall structures and valleys.

Classification: Applying this method to a larger area, mountain ridges are delineated together with moraine structures. These areas can be distinguished by calculating the mean slope within the voronoi diagram polygons.

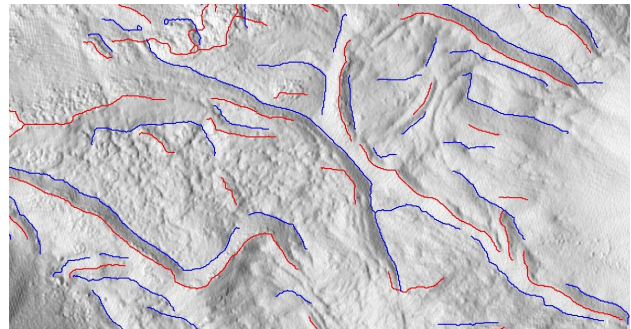


Figure 5. Moraine complex with line segments (red - upper edges, blue - lower edges)

4. CONCLUSION AND OUTLOOK

The presented work shows that ALS data provides important information on surface objects. The advantage of an object-based approach is the additional information on object geometry and object relations which increases the possibilities in the analysis. The connection of classification results and the 3D information of the ALS data give new possibilities for applications in natural hazard management and modelling.

Future work will focus on a) the handling of line objects and b) the use of polygon segments directly derived from the original 3D ALS point cloud.

5. REFERENCES

- Arge, L., Chase, J.S., Halpin, P.N., Toma, L., Vitter, J.S., Urban, D., Wickremesinghe, R., 2001. Flow computation on massive grids. In: Aref W.G. (Ed.), *Proceedings of the Ninth ACM International Symposium on Advances in Geographic Information Systems*, pp. 82-87.
- Asselen, S., Seijmonsbergen, A.C., 2006. Expert-driven semi-automated geomorphological mapping for a mountainous area using a laser DTM. In: *Geomorphology*, in press.
- Benz, U., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. In: *ISPRS Journal of Photogrammetry and Remote Sensing*, 58, pp. 239-258.
- Blaschke, T., 2005. Towards a framework for change detection based on image objects. In: Erasmi, S., Cyffka, B., Kappas, M. (Eds.), *Remote Sensing & GIS for Environmental Studies*, 113, pp. 1-9.
- Filin, S., Pfeifer, N., 2006. Segmentation of airborne laser scanning data using a slope adaptive neighborhood. In: *ISPRS Journal of Photogrammetry & Remote Sensing*, 60, pp. 71-80.
- Glenn, N.F., Streutker, D.R., Chadwick, D.J., Tackray, G.D., Dorsch, S.J., 2006. Analysis of LiDAR-derived topographic information for characterizing and differentiating landslide morphology and activity. In: *Geomorphology*, 73, pp. 131-148.
- GRASS Development Team, 2006. Geographic Resources Analysis Support System (GRASS), GNU General Public License. ITC-irst, Trento, Italy. <http://grass.itc.it> (accessed 20 June 2006)

- Höfle, B., Rutzinger, M., Geist, T., Stötter, J., 2006. Using airborne laser scanning data in urban data management - set up of a flexible information system with open source components. In: Fendel, E., Rumor, M. (Eds.), *Proceedings of UDMS '06, 25th Urban Data Management Symposium*, on CD.
- Hübl, J., Kienholz, H., Loipersberger, A. (Eds.), 2002. *DOMODIS: Documentation of Mountain Disasters*. Intraprevent, Klagenfurt.
- Kääb, A., Huggel, C., Fischer, L., Guex, S., Paul, F., Roer, I., Salzmann, N., Schäferli, S., Schmutz, K., Schneider, D., Strozzi, T., Weidmann, Y., 2005. Remote sensing of glacier- and permafrost-related hazards in high mountains: an overview. In: *Natural Hazards and Earth System Sciences*, 5, pp. 527-554.
- Kerschner, H., 1993. Späteiszeitliche Gletscherstände im südlichen Karwendel bei Innsbruck, Tirol. In: Petermüller-Strobl, M., Stötter, J. (Eds.), *Innsbrucker Geographische Studien* Bd.20: Der Geograph im Hochgebirge (Heuberger-Festschrift), pp. 47-55.
- Mayya, N., Rajan, V.T., 1994. Voronoi Diagrams of Polygons: A Framework for Shape Representation. In: *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 638-643.
- McKean, J., Roering, J., 2004. Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry. In: *Geomorphology*, 57, pp. 331-351.
- Neteler, M., Mitasova H., 2004. *Open Source GIS: A GRASS GIS Approach. 2nd Edition*. Kluwer Academic Publishers, Boston, pp. 271-282.
- Oude Elberink, S., Maas, H.-G., 2000. The use of anisotropic height texture measures for the segmentation of airborne laser scanner data. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Amsterdam, the Netherlands, Vol. XXXIII, Part B3/2, pp. 678-684.
- Python Software Foundation, 2006. Python Programming Language. <http://www.python.org> (accessed 20 June 2006)
- Rottensteiner, F., Trinder, J., Clode, S., Kubik, K., 2005. Automated delineation of roof planes from LIDAR data. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Enschede, the Netherlands, Vol. XXXVI, Part 3/W19, pp. 221-226.
- Rutzinger, M., Höfle, B., Geist, T., Stötter, J., 2006. Object-based building detection in airborne laser scanning data within GRASS GIS environment. In: Fendel, E., Rumor, M. (Eds.), *Proceedings of UDMS '06, 25th Urban Data Management Symposium*, on CD.
- Sithole, G., 2005. *Segmentation and Classification of Airborne Laser Scanner Data*. Publications on Geodesy of the Netherlands Commission of Geodesy, 59, Delft, pp. 93-118.
- Tóvári, D., Vögtle, T., 2004. Classification methods for 3D objects in laserscanning data. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36, Istanbul, Turkey, Vol. XXXV, Part B3. <http://www.isprs.org/istanbul2004/comm3/papers/304.pdf> (accessed 20 June 2006)
- Vosselman, G., Gorte, B., Sithole, G., Rabbani, T., 2004. Recognising Structure in Laser-Scanner Point Clouds. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Vol. XXXVI, Part 8/W2, Freiburg, Germany, pp. 33-38.
- Wagner, W., Eberhöfer, C., Hollaus, M., Summer, G., 2004. Robust filtering of airborne laser scanner data for vegetation analysis. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Freiburg, Germany, Vol. XXXVI, Part 8/W2, pp. 56-61.
- Wehr, A., Lohr, U., 1999. Airborne laser scanning - an introduction and overview. In: *ISPRS Journal of Photogrammetry and Remote Sensing*, 54, pp. 68-82.
- Wood, J.D., 1996. The geomorphological characterisation of digital elevation models PhD Thesis, University of Leicester, UK. <http://www.soi.city.ac.uk/~jwo/phd> (accessed 20 June 2006)