OBJECT-BASED BUILDING DETECTION BASED ON AIRBORNE LASER SCANNING DATA WITHIN GRASS GIS ENVIRONMENT

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ABSTRACT

The paper gives insight into the workflow of a building detection algorithm analysing airborne laser scanning data based on open source software. The procedure is set up in the GRASS GIS environment. Buildings are exclusively extracted from airborne laser scanning data and its derivatives without using any additional data source (e.g. high resolution images). This shows the potential but also the limitations of this kind of data. The implemented object-based approach uses remote sensing and GIS methods. Buildings are landscape objects with a well defined border. The object-based approach works on sharp outlines of objects which is an advantage in the case of building detection.

1 INTRODUCTION/MOTIVATION

The work presented here is part of a research project at the alpS - Centre for Natural Hazard Management, Innsbruck/Austria. The project aims at the use of airborne laser scanning data for different aspects in natural hazard management. According to the philosophy of alpS as a platform for interdisciplinary and applied research, the project consortium comprises scientific partners as well as public authorities and private companies giving the project a high practical relevance. In the project, emphasis is laid on the qualitative assessment and on the quantification of surface properties, object recognition as well as the temporal change of these properties.
Building detection as a special task in object recognition is the first analyse step for the further use of object parameters in different applications. Recent applications of building detection using Airborne Laser Scanning (ALS) data are 3D city modelling (*Brenner, 2005*), volume calculation for the determination of heat requirements (*Neidhart and Brenner, 2003*) or the delineation of building roof facettes for defining potential areas for photovoltaics

(*Vögtle et al., 2005*). In the field of natural hazard research an emphasis lies on the integration of roughness values of buildings in for example avalanche simulation models (*Sailer and Kleemayr, 2005*). Beside the integration of building parameters into process models there is a demand of these parameters for the estimation of damage potential related to natural hazard risk (*Keiler et al., 2004*).
The motivation of this work is to create a workflow for object detection within an open source environment which can be used to detect building objects by using the height information of ALS data.
Public administrations are, on the one hand, responsible for spatial data management, on the other hand they are the first users analysing the data. Several projects show that ALS technology is an operational method to maintain accurate survey information with a wide spread field of application (*Wack and Stelzl, 2005; Rieger et al., 2005*). The growing use of open source software by public administrations, like for example Vienna (*Wienux, 2005*) or Munich (*LiMux, 2005*), and even the use for surveying and geoinformation tasks (*Thoenissen et al., 2005; Duijnmayer, 2005*) show the need for open source analyse tools. A further example is the city of Genova testing GRASS for the geoinformation management in public services (*Ghosh, 2005*). One of the main reasons for the growing interest in both automated ALS data analysis and open source technology is cost efficiency. This is also shown by the EuroSDR comparison of 3D city models (*Kaartinen et al., 2005*) were decreasing costs by automatisation in building extraction was one central argument in the study.

2 RELATED WORK

2.1 Object based image analysis (OBIA)

The OBIA approach tries to solve problems appearing in classification of high resolution remote sensing data. The high spatial resolution makes it necessary to distinguish between many different object types like in case of a building: roof windows, chimneys, and roof bricks while the object of interest "building" would be a hierarchical higher class of all these subclasses. Furthermore, there are pixels of uncertainty or wrong classified pixels between two objects known as the "salt and pepper" effect. OBIA compensates these problems by considering object features and topology. Based on an initial segmentation the single segments (i.e. sets of pixels) containing information about pixel values, object shape and topology are the input in the classification step (*Benz et al., 2004*).
Segmentation means the delineation of homogenous regions in a data set. These segments, also called object primitives, are the input for the object classification. As the classified objects of interest can be used seamlessly in a GIS OBIA is known as a technique combining remote sensing and GIS analyses.
Recent applications focus on the use in ecology, habitat delineation and land use classification (*Blaschke, 2005*). Although there are different approaches (*Lang, 2005*), methods (*Hay et al.,*

2003) and software products (*Meinel and Neubert, 2004*) in the field of OBIA, for most of the applications the commercial Software eCognition is used (*Benz et al., 2004*). It provides region growing segmentation and a knowledge-based fuzzy rule base for classification.
In the field of ALS and building recognition *Lemp and Weidner (2005)* use a combination of hyperspectral data and geometrical information from ALS data to classify an urban test site. Segmentation was done by testing different weights on colour and geometrical input layer in eCognition. The use of geometrical information could enhance the delineation of roof facets. *Hofmann et al. (2002)* use eCognition to segment ALS height data. The segments are exported into a GIS for further analysis towards computation of object features and final classification. *Tòvàri and Vögtle (2004)* use eCognition as well for classification of bare earth, vegetation and buildings using ALS data.

2.2 Building detection with ALS data

The recent approaches for automated building detection can be divided into three groups depending on the input data type: point cloud segmentation, gridded ALS data and derivatives, and combined datasets (additional GIS layer or digital aerial images).
Maas and Vosselman (1999) present two methods to derive buildings from ALS raw data by analysing invariant moments in the ALS point cloud and to derive plane faces by triangulation.
Research activities are mainly concentrated on building detection by using a combination of digital aerial images and ALS data to overcome the problem of distinguishing trees from buildings.
Rottensteiner et al. (2005b) describe a workflow delineating and reconstructing roof facets exclusively from ALS data. Planes are detected by region growing of the DSM. The outlines are defined and enhanced by considering neighbourhood relations of the planes and the detection of height changes in the DSM. The rules for the enhancement of the results rely mainly on statistical tests.
Rottensteiner et al. (2005a) show different performances of building classification based on the probabilistic classification approach of Dempster-Shafer depending on various combinations of first pulse and last pulse DSM (Digital Surface Model), DTM (Digital Terrain Model) derived from raw ALS points and NDVI (Normalised Difference Vegetation Index) derived from orthophotos. The comparison of results shows that the classification correctness is strongly related to the building size.
Vozikis (2004) uses a nDSM (normalized Digital Surface Model) representing object heights derived from ALS points and an orthophoto with higher resolution. The dataset is segmented by iterative region growing. The final building outlines are defined by an iterative Hough transformation.
Zhou et al. (2004) segment an orthophoto using standard image processing methods in order to detect object edges. Buildings and vegetation are distinguished using the information in the ALS data.

In general using data combinations raises the possibilities for the detection of buildings. While building edges can be derived from images, information on the surface can be taken from ALS data. Furthermore, existing data from cadastral maps can provide additional information in the detection workflow. On the other hand using additional data for delineation, classification or selection of regions of interests is also connected with problems based on different spatial representation of objects depending on the method of data collection and the time of data collection. The datasets can contain deformed, additional or missing objects (*Blaschke, 2005*). To overcome these problems the aim is to find detection workflows within consistent datasets.

3 TEST SITE AND DATASETS

The test site is located in and around the city of Hohenems (Vorarlberg/Austria) with an area of 10.44 km^2. The area consists of different land cover types such as built-up areas, forests and agricultural land as well as infrastructure elements like railroads, highways and power lines. The built-up areas comprise dense residential areas, single occupancy houses with gardens and trees and large industrial buildings.

The used data was acquired in leave-off season (November 2003) with an ALTM 2050 Optech scanner. The average point density in the test site is 16 pt/m^2. The raw laser points are stored in an ALS Information System with which the DSM (32.5 MB) and a First Last Pulse Difference Model (FLDM) (16.3 MB) in 1m resolution are generated. The FLDM contains the gridded distance information between first and last reflection of every single laser pulse (*Höfle et al., 2005*). Maintaining significant edges and minimising the degree of interpolation are key requisites for a successful segmentation based on height information. On the one hand a high point density guarantees a better description of edges (*Maas and Vosselman, 1999*) but on the other hand it is important to use an edge preserving algorithm for raster generation (*Höfle et al., 2006*). Areas with no reflection information (e.g. water surfaces) are closed by the use of a median filter.

A rasterised and resampled 2D GIS building layer of the digital cadastral map (DCM) of Vorarlberg/Austria with 1 m resolution is used as reference data (*Amt der Vorarlberger Landesregierung, 2005*).

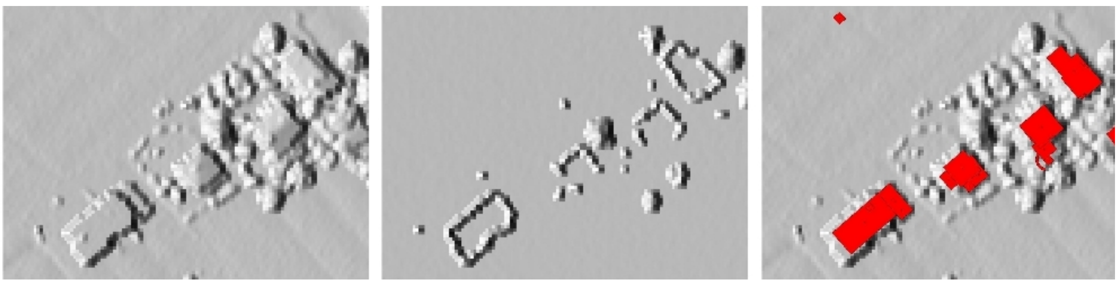

Figure 1: Input data sets (Digital Surface Model, First Last Pulse Difference Model, and Digital Cadastral Map).

4 METHOD

Although this approach can work with different input data types, in the following investigation only ALS data and its derivatives are used as input data sets for reasons of consistency (see chapter 2).

4.1 GRASS and LINUX environment

The geographical information system GRASS (Geographical Resources Analysis Support System) is a multifunctional open source GIS published under GNU General Public License. It comprises analysing, image processing and visualisation modules for both raster and vector data. The user can operate in both GUI and command line. The use of LINUX and GRASS in command line mode allows to automate GRASS functionalities in UNIX shell scripts and develop new modules within this environment (*Neteler and Mitasova, 2004*).

4.2 Workflow

The workflow of OBIA for ALS data is implemented in four modules which can be used independently as GRASS commands for the detection of different object types. The first step is the image segmentation, detecting discontinuities in the input data set. The input data is divided into so called object primitives which can be parts of or whole semantic meaningful objects. Based on the segments a set of object features describing the objects is calculated (second module). These features are the input for the classification (third step) which is based on a threshold rule base. The results are checked by a fourth module, the error assessment module. Parameters for further modelling can be calculated on the basis of the classification results.
The modular workflow makes a flexible use possible. Segmentation results from other software products can be imported and classified in the GRASS environment. Each other GRASS standard function can be used instead or in addition to the current workflow. The classification tools of GRASS (e.g. maximum likelihood algorithm) can be used to classify the segments as well.

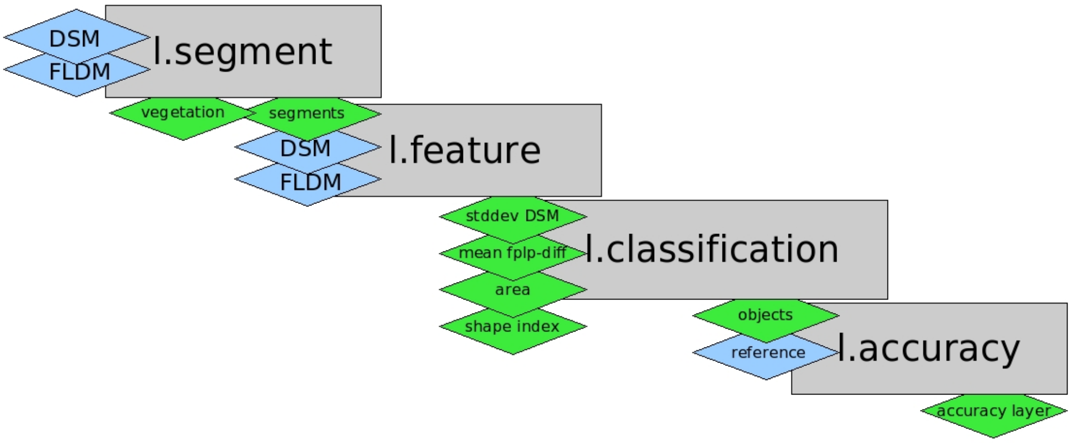

Figure 2: Workflow of OBIA modules with input and output data.

4.2.1 Segmentation and enhancement

The segmentation module requires a DSM and, optional, a FLDM as input datasets. In the current version two different segmentation methods (moving window and fill sinks) are implemented.

The moving window method detects break lines by a user defined height threshold in the DSM using a 3x3 neighbourhood. These discontinuities correspond to the border of object primitives: objects and terrain edges as well. In case the segments are not closed properly, gaps in the outlines are closed by a blow and shrink procedure. The user has several tuning options and can choose the minimum height threshold for break line detection and the number of iterations of blow and shrink for segment enhancement.

The second segmentation method is based on a fill sinks algorithm (*Arge et al., 2001*). Therefore, the DSM is inverted and the filling of sinks is performed as it is common for flow computations. The new calculated filled DSM is subtracted by the original one to maintain a kind of a nDSM (normalised Digital Terrain Model) containing object heights. Using this delineation method the user has to specify a height threshold to remove artefacts caused by low terrain in the surrounding of the objects of interest.

A common problem in building detection algorithms is the distinguishing between high vegetation and buildings. Especially tree crowns which are directly connected to a building roof are difficult to delineate (*Rottensteiner et al., 2005b*). To overcome this problem the segmentation module provides a vegetation removal tool. Therefore a vegetation mask is calculated from the FLDM. The quality of the vegetation mask is strongly dependent on the point density. The FLDM represent the height difference between first and last reflection of every laser pulse. The minimum distance of the first and last reflection which can be

measured by the sensor is about 1.5 m (*Kraus, 2004)*. This means that the FLDM contains objects like vegetation, building edges and power lines higher than around 1.5 m.
Tests have shown that it is not possible to generate building outlines from building edges directly from the FLDM. The variation and completeness of these edges depend strongly on footprint size, scan geometry and point density. The use of building edges extracted out of the FLDM would require a higher point density than it was available for this test site. Power lines and building edges are represented as very thin and incomplete objects in the FLDM and can be removed by a high pass filter so that only vegetated areas remain. Tests with different pixel neighbourhoods showed that a simple 4-neighbourhood removes most disturbing edges and lines while preserving vegetation best. The gaps which grow by filtering are closed with a single cell buffer around the remaining vegetation. In the end the obtained vegetation mask is subtracted from the delineated objects. Until this stage there are still segments in the object primitive layer which are not supposed to be building objects (e.g. parts of vegetation or terrain). Some of these segments are removed with an area criterion. The output of the segmentation module is a raster layer with allocated unique IDs containing object primitives.

4.2.2 Feature and parameter calculation

The module for object feature calculation provides the necessary information for each segment to build up and distinguish the final objects in the classification step. As input a segment layer (object primitives) with IDs is required. This could be also a segmentation from another software. Stand-alone features like shape or size are calculated exclusively out of the segments (*Baker, 2001*). Dependent features need additional datasets like DSM or FLDM. The module is not limited to these two input data types, thematic GIS raster layers or optical imagery data can be used as well.

feature	***formula***	***required input***
stddev of object height	$\sigma=\sqrt{\frac{1}{(n-1)}\sum_{p=1}^{n}(x_p-\mu)^2}$	DSM
average of fplp-difference	$\mu=\frac{1}{n}\sum_{p=1}^{n}x_p$	FLDM
stddev of aspect	$\sigma=\sqrt{\frac{1}{(n-1)}\sum_{p=1}^{n}(\beta_p-\mu)^2}$	DSM
shape index: perimeter per area	$pa=\frac{perimeter}{area}$	no additional input required

feature	formula	required input
shape index: related circumscribing circle	$rcc=\frac{2*(\frac{area}{\pi})^{0.5}}{(longest\ axis)}$	no additional input required

Table 1: Selected stand-alone and dependent features.

Two different kinds of shape indices for feature calculation are implemented (Table 1). The shape index calculated as the ratio of perimeter and area of every object shows significant differences between regular, man-made objects like buildings and irregular shaped, natural objects like parts of vegetation or terrain. This index varies with object size. Therefore it is possible to calculate the related circumscribing circle shape index. It compares the area of the object with the smallest circle that circumscribes the object (*Baker, 2001*).
The mean standard deviation of height values within a segment is a well suited feature to describe surface roughness. While vegetation also below 1.5 m shows a high roughness, buildings depending on their roof structure have a relatively low roughness value. The difference between first pulse and last pulse is another useful feature for distinguishing buildings from remained segments belonging to vegetation, building edges or power lines.

4.2.3 Classification

The classification is based on crisp threshold values for the features. A correct classification is provided by displaying the histogram and basic statistics for each feature layer. Furthermore, the feature layer itself is displayed with a standard colour table and the values for every segment can be queried interactively.
Remaining terrain segments are removed with the goo-option (ground or object) which checks the neighbourhood for each segment if the surrounding is higher or lower in mean elevation than within the segment. Lower surrounding is an indicator for a high object while higher surrounding indicates a terrain segment which can be removed.
Good classification results can be obtained if features and their statistics are calculated for the reference data set as a kind of workflow calibration. In this way the distribution of feature values within the reference objects can be seen.

4.2.4 Error assessment

The error assessment is carried out with a reference dataset maintaining the objects of interest. Both user's (UA) and producer's accuracy (PA) are calculated for the whole test site (*Richards and Xiuping, 2006*). In addition the number of classified objects and the number of objects in the reference dataset is shown in the output. Successful detected objects are defined as classified objects touching reference objects if a overlay with logical AND is performed. A stable classification result is indicated by a close distance of UA and PA values. The over- and underestimation of the classification is stored in a separate layer for visualizing the classification result.

5 Results and Discussion

The two main parameters for data segmentation are the minimum area of segments and the height threshold while in the classification step the used features and the chosen thresholds determine the classification results. The minimum area was applied to both the segments and the reference dataset. Figure 3 shows the decreasing number of classified objects in correspondence to the applied minimum area. The data was segmented with both methods (moving window and fill sinks) with a minimum area criterion from 50 m² to 300 m² and height thresholds from 1 m to 5 m. Table 2 shows the used classification features and classification thresholds. The min-95p (minimum and 95 percentile) and the min-max values (minimum and maximum) were generated from the reference dataset, while the knowledge-based minimum and maximum thresholds were determined by a manual inspection of the calculated features based on the derived segments.

feature	***min-95p***	***min-max***	***knowledge-based***
fplp-difference [m]	0 - 1.47	0 - 35.4	0.5 - 3
stddev height [m]	0.04 - 4.09	0 - 51.1	0.04 - 4.09
shape index (p/a) [m^{-1}]	0.07 - 0.55	0 - 1.8	0 -0.6

Table 2: Used classification features and thresholds.

After segmentation and classification the error values and the quality raster for over- and underestimation is calculated. The comparison of the calculated UA and PA for each method and parameter setting is illustrated in Figure 4. In general, the best results are achieved with a minimum area of 100 m² and object height thresholds between 2 m and 3 m.

The moving window segmentation was carried out with a single iteration of blow and shrink for segment closing. The more iterations are executed the more deformed the objects outline gets. With a height threshold of 2 m and a minimum area of 100 m² this approach classified 61% of the reference building pixels right (PA) and 66% of the classified pixels are successfully classified (UA) using the knowledge-based classification thresholds.

The fill sinks segmentation provides already building outlines containing few segments which do not belong to other object classes (e.g. low vegetation). For this segmentation method no classification method could improve the classification results. The variation of the feature values within building segments was too high, so that it was not possible to remove wrong delineated segments by classification without loosing building objects. The raw segments gained with thresholds of 3 m object height and 100 m² minimum area lead to 78% PA and 73% UA.

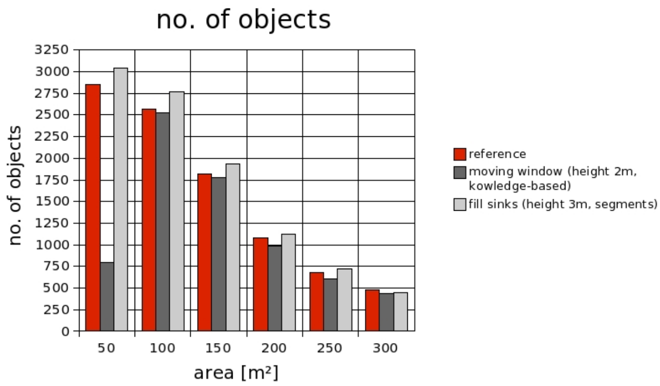

Figure 3: Number of detected objects depending on minimum area.

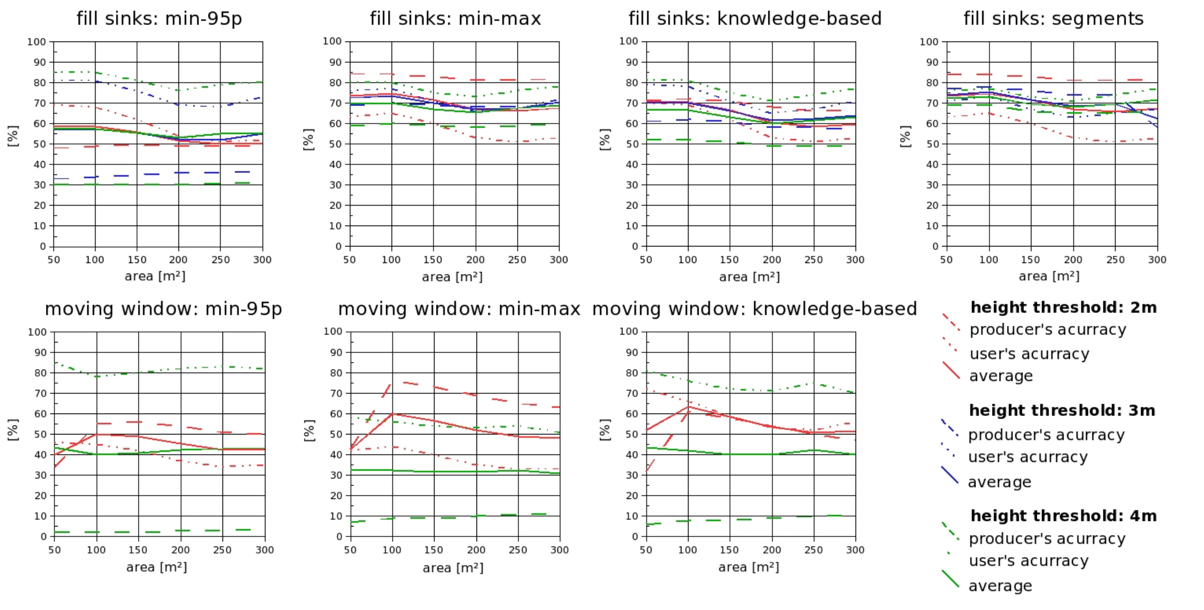

Figure 4: Error assessment dependent on area, height and classification thresholds.

The examples in Figure 5 explain the wrong classified pixels and missing objects. First of all the successful classified objects suffer from a slight over estimation because the objects in the DSM are not represented with steep edges but with sloped transitions. Sample [a] and [d]

show the problem that buildings marked in the reference dataset are not represented in the DSM, leading to a low PA. On the other hand there are buildings which are not detected by the used methods (samples [c] and [f]). Additionally there are new build objects which are not represented in the reference dataset leading to a low UA which is shown in sample [b] and [e].
While small roof objects like antennas or chimneys have no influence to the fill sinks segmentation method, it is effected by the influence of high neighbouring objects and changes in surrounding terrain. This can lead to both over and under estimation in the segmentation step.
For both segmentation methods the vegetation removal option by generating a vegetation mask out of the FLDM was applied. With this option most trees attached to buildings could be removed.

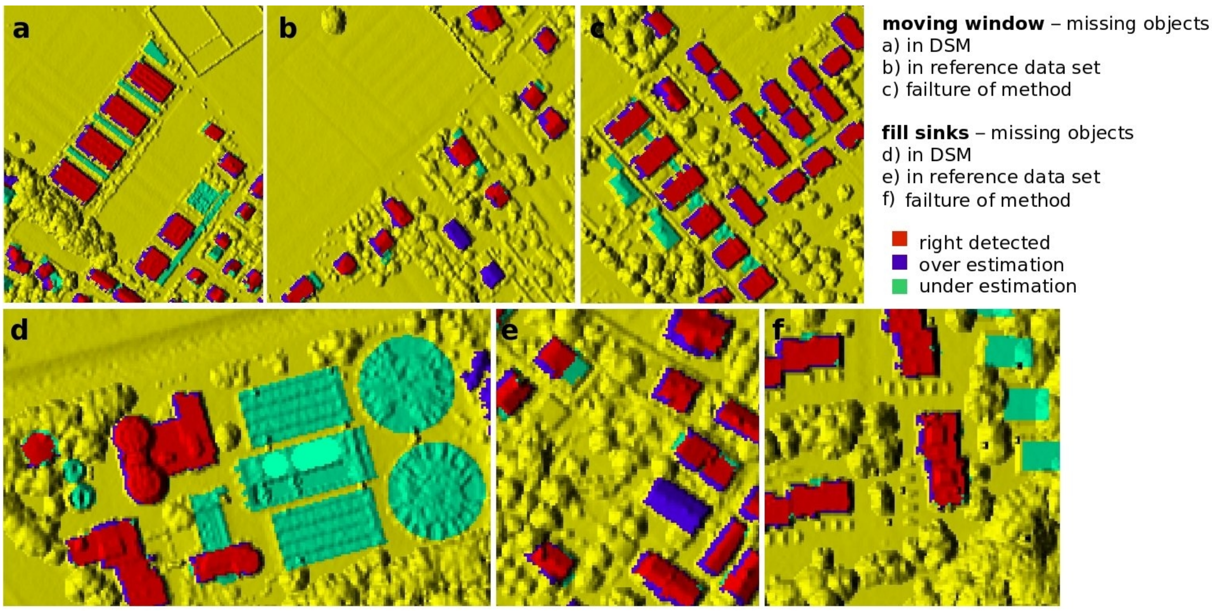

Figure 5: Examples for over and under estimation of classification results.

6 Conclusion and Outlook

The workflow presented here is a first step to implement an OBIA approach for ALS data in an open source information system. The results were gained by ALS input data only. Future work will focus on the enhancement of this first classification results to provide an operational classification tool. Further testing of new object features is necessary to find the best object description. The concept has an open design and therefore new algorithms, features and classification modules can be adapted and integrated easily. Further work will be

also the adaptation of the workflow to other object types and the transfer of the classification results back to the ALS point cloud.
The existing methods like the moving window method suffer from not closed segments by the blow and shrink procedure. For example the generation of building outlines by a Hough transformation (*Vozikis, 2004*) could improve this segmentation method.
In the current stage the results can be used in further applications like the automated production of cartographic layers (high vegetation and buildings). These thematic layers can also provide input on roughness for avalanche or flood modelling.

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