In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents   Author Index   Keyword Index

CHANGE DETECTION OF BUILDING FOOTPRINTS FROM AIRBORNE LASER SCANNING ACQUIRED IN SHORT TIME INTERVALS

M. Rutzinger [a, *], B. Rüf [b,c], B. Höfle [d], M. Vetter [e]

[a] ITC - Faculty of Geo-Information Science and Earth Observation of the University of Twente, 7500 AA Enschede, The Netherlands - rutzinger@itc.nl
[b] alpS-Centre for Natural Hazard Management, 6020 Innsbruck, Austria
[c] University of Innsbruck, Department of Geography, 6020 Innsbruck, Austria - benno.ruef@uibk.ac.at
[d] University of Heidelberg, Department of Geography, 69120 Heidelberg, Germany - hoefle@uni-heidelberg.de
[e] Vienna University of Technology, Institute of Photogrammetry and Remote Sensing, 1040 Vienna, Austria - mv@ipf.tuwien.ac.at

Commission VII

KEY WORDS: Airborne laser scanning, building segments, classification, object-based change detection, urban areas

ABSTRACT:

Several recent studies have shown that airborne laser scanning (ALS) of urban areas delivers valuable information for 3D city modelling and map updating. Building footprint detection from multi-temporal ALS lacks in comparability because of changing ALS flight parameters, flying season, interpolation settings if digital elevation models are used, and the ability of the used building detection method to deal with these influences. So far, less attention has been paid to change detection of buildings within a short time span (approx. three months), where major problems are the high variability of vegetation over time and to distinguish temporary objects from small changes of buildings, which are currently under construction and demolition, respectively. We introduce an object-based workflow to investigate how unchanged objects can be defined, which variability in the object appearance is allowed to define an object as unchanged, and at which threshold a change can be indicated. The test site is situated in the city of Innsbruck (Austria) where ALS data is available from summer and autumn in 2005. In an initial step building footprints are derived by an object-based image analysis (OBIA) detection method for each flight independently. The parameters for building detection are derived for a training site in order to automatically derive the rules of the classification tree. Then the object features of buildings derived from the different flights are compared to each other and separated into the classes unchanged building, new building, demolished building, new building part, and demolished building part. The results are verified by a reference, which was created manually by visual inspection of the elevation difference image of both epochs. For new buildings and building parts 90% and for demolished buildings and building parts 32% were detected correctly. The detection of demolished buildings is strongly influenced by the appearance of high vegetation, which is caused by the decreasing heights of trees by comparing summer (leaf-on) and autumn (leaf-off) ALS data.

1. INTRODUCTION

Urban areas are highly dynamic landscapes where changes occur in different rates and frequencies. Nowadays airborne laser scanning (ALS) data is available for several urban areas in Europe. The purpose of acquiring multi-temporal ALS data is on the one hand to have the most recent surface representation of a certain area and on the other hand to be able to perform change detection analysis for monitoring purposes. Change detection plays a key role in urban planning i.e. monitoring of urban sprawl and its dynamics (e.g. Durieux et al, 2008; Maktav et al., 2005) and to detect changes after natural hazards such as earthquakes (e.g. Vu et al., 2004; Rehor et al., 2008).

The objective of this paper is to show how changes appear in ALS data, caused by either seasonal differences or by urban dynamics i.e. construction activities. It is interesting to see how these changes are captured in data, which was flown within only three months, which is a very short time period for urban multi-temporal ALS data sets. The aim is to explore the performance of multi-temporal building detection by applying the method of Rutzinger et al. (2006).

2. RELATED WORK

Champion et al. (2009) test four different building detection approaches (Champion, 2007; Matikainen et al., 2007; Olsen and Kudsen, 2005; and Rottensteiner, 2008). The input data were infrared orthophotos and digital surface models (DSMs) from image matching and for one test site from ALS. A comprehensive comparison was undertaken in order to investigate the impact of input data types, resolution, scene complexity and methods. The authors state that high quality DSMs are important for reliable building and change detection. However, the ALS data available in this study was first echo data, which made it difficult to differentiate buildings from vegetation. The detection of changing buildings in ALS DSMs was already early investigated by Murakami et al. (1999) by subtracting two DSMs and filtering the difference image in

---

* Corresponding author.

In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents　　　　　Author Index　　　　　Keyword Index

order to remove elevation differences along edges of unchanged buildings. A building change detection method using exclusively ALS data in an object-based approach was presented by Vögtle and Steinle (2004). Vosselman et al. (2004) developed a method for updating cadastral maps by detecting buildings from ALS data and comparing them to an existing building footprint database. Further work on building footprint extraction and changed detection such as combining aerial images with ALS DTMs or using more recent remote sensing data for updating of existing cadastral maps is not reviewed here since the work presented focuses on the usage of ALS data only. However, for a comprehensive overview of related work on building footprint detection methods and building change detection the reader is referred to the recently published article by Matikainen et al. (2010).

3. TEST SITE AND DATA SETS

3.1 Test site

The test site covers the major part of the city centre of Innsbruck (Austria). It comprises a densely built-up area with varying building types (multi-story block buildings, single family houses with gardens, large industrial buildings), agricultural land, and forested areas. The data sets also contain temporary objects such as cars, trains, market booths, etc. which appear as changes in the data (Fig. 2).

3.2 Data sets

The ALS data were acquired as pilot surveys for the laser scanning project Tyrol, Austria (Anegg, 2007). The two data sets overlap the major part of the city of Innsbruck, the city centre and parts to the west including the airport (Fig. 1). The overlapping area represents the border of two larger ALS campaigns in the north (summer scan) and south (autumn scan). Both flights were acquired with an Optech ALTM 2050. The average point density of both flights is around 4 pts/sqm. The test site covers an area of 10 km^2 and contains 2441 building footprints in the summer data set.
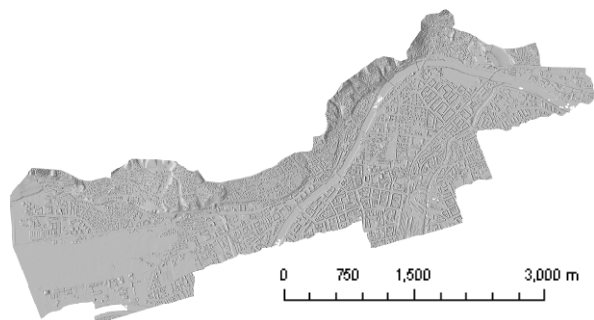

Fig. 1. Shaded relief map of the last echo DSM of the autumn flight showing the test site of Innsbruck (Austria) where multi-temporal airborne laser scanning data is available

3.3 Change detection

As a manual reference a difference raster (diffDSM) of both DSMs was calculated, which visualizes all differences in elevation, which might disturb the building change detection procedure. Figure 2 shows in green areas, where the elevation decreased and in red, where the elevation increased.

First of all, building edges show increases and decreases, indicating here a shift to north west, which can be caused by (i) insufficient registration of the data, (ii) difference of scan angle in both scans and therefore different amount of echoes on building walls, and (iii) different echo distribution and local point density which effects the aggregation of points to raster cells when calculating the DSM. Further decreases are reasoned by parking cars, umbrellas in front of restaurants in the inner city, which were removed in the autumn scan (Fig. 2, lower arrow), maize fields, which were harvested, and deciduous trees, which lost their leafs. While in the summer scan the laser beam was reflected on the tree canopy, in the autumn scan the laser beam was reflected on the branches or even on the ground, which leads to negative heights in the diffDSM. An increase of elevation can be found in the city centre where the Christmas tree for the Christmas market was already installed (Fig. 2, upper arrow).
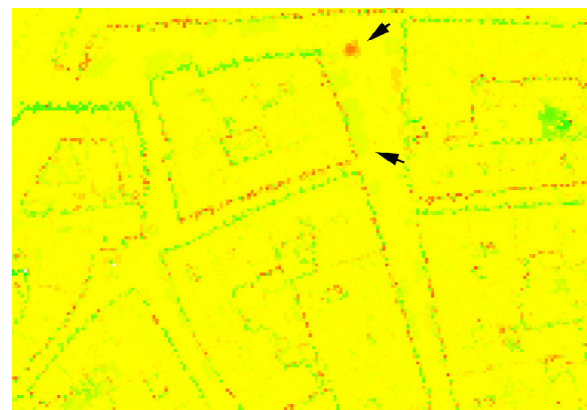

Fig. 2. Different aspects on elevation changes in the difference digital surface model from the city centre

4. METHOD

The workflow of the proposed building change detection comprises two major steps, which are firstly the object-based building footprint detection (Sect. 4.1), which is applied for each laser scan independently and secondly the change detection procedure (Sect. 4.2).

4.1 Extraction of building footprints

In a first step a first-last-echo difference model (FLDM) is calculated, by subtracting the last reflection (lowest elevation) from the first reflection with the highest elevation in order to derive a vegetation mask. Elevation differences of reflections within a single laser beam mainly occur at the canopy of high vegetation and building edges. Hence, the difference model is further enhanced by applying a filter for removing long thin structures representing building edges and small areas (Fig. 3). The areas covered by the vegetation mask are set to "no data" and are not considered any more in the building detection process.

In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents   Author Index   Keyword Index
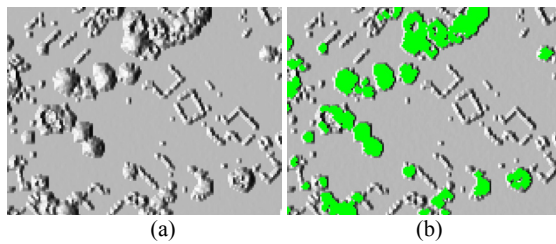

<center>(a)   (b)</center>

Fig. 3. (a) First-last-echo difference model and (b) the derived enhanced vegetation mask

Next, building regions are segmented by inverting the DSM and applying a fill sinks procedure (Arge et al., 2001; GRASS Development Team, 2010). All high objects are considered as sinks and filled up to the minimum elevation in the individual region in order to guarantee a hydrologically consistent elevation model. This model is subtracted from the original DSM and thresholded at a certain minimum height in order to remove artefacts, i.e. overestimation of building outlines or the influence of low vegetation (Fig. 4).
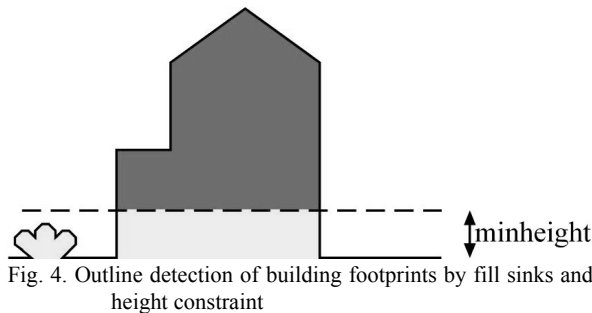

Fig. 4. Outline detection of building footprints by fill sinks and height constraint

The remaining building segments are enhanced by applying a morphological opening, which further smoothes and removes remaining overestimation of the building outlines (Fig. 5).
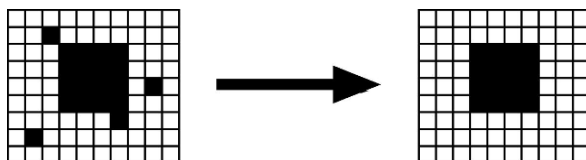

Fig. 5. Outline enhancement by morphological opening.

The segments are classified into buildings and non-buildings using a classification tree (Breiman et al., 1993; Maindonald and Braun, 2007) derived from a training area. As training segments building footprints and non-building segments are selected from the derived segments. For those, several statistical features such as first order statistic on elevation, object heights, first-last-echo difference, standard deviation of slope and aspect derived from the DSM, and geometrical object properties such as area and shape indices. Table 1 lists all the input features which were calculated to build up the classification tree.

By applying the classification tree (Therneau and Atkinson, 1997) the sample set is divided into subsets which are tested and compared in order to define the optimal splitting rule between both classes. In fact, the developed rule base is a box-classifier in feature space, which has crisp thresholds at each node (rule). The features can occur in multiple hierarchies of the classification tree. The levels, i.e. the complexity of the classification tree, can be regulated by defining a complexity parameter, which is also known as pruning. In general, the complexity of a classification tree should be kept minimal in order to avoid modelling the data itself instead of describing the class specific characteristics.

Object Feature	DSM	FLDM	Segments
Stdev object height	X		
Mean object height	X		
Max object height	X		
Min object height	X		
Mean FLDM		X	
Area			X
Shape (perimeter/area)		X	X
Shape (circumscribing circle)		X	X
Stdev slope	X		
Stdev curvature	X		

Table 1. Object features calculated as classification input

4.2 Change detection

The building change detection procedure is based on the automatically extracted building footprints and their attributes exclusively. The procedure distinguishes the following cases:

- unchanged building or building part
- new building
- demolished building
- new building part
- demolished building part

The change detection compares spatially related building footprints and their attributes derived from each epoch individually. In order to be able to detect also gradual changes at buildings such as the construction of a new story, not only the appearance of another object polygon is checked but also the mean difference of the elevation in the segment part. There are several methods how to measure detection success of building footprint extraction (Rutzinger et al., 2009) In the following the change detection results are evaluated by calculating the overall accuracy as

$$\text{overall accuracy} = TP / (TP+FP+FN) \quad (1)$$

with true positives (TP), which are segment parts classified as change which are also changes in the reference and the false positives (FP), which are segment parts classified as change where no changes occur in the reference. False negatives (FN) are changes which are in the reference but are not detected by the method.

5. RESULTS

5.1 Building detection

The vegetation mask is derived for both input data sets and then merged in order to get maximum vegetated area. The building segments from both epochs are derived by the fill sinks approach (Sect. 4.1) and were further selected by a minimum height of 2.5 m and minimum area of 10 sqm. The shape of the

In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents | Author Index | Keyword Index

building segments is enhanced using morphological opening of 3 m and 4 m kernel size, respectively. For a training area containing 103 buildings two classification trees were derived independently. The features automatically selected for classification were area, shape index, and first-last-echo difference. The complexity of the derived trees is very low. The trees consist of one and two splitting nodes, respectively. Figure 6 shows a subsection of the classified building footprints from the autumn data set.
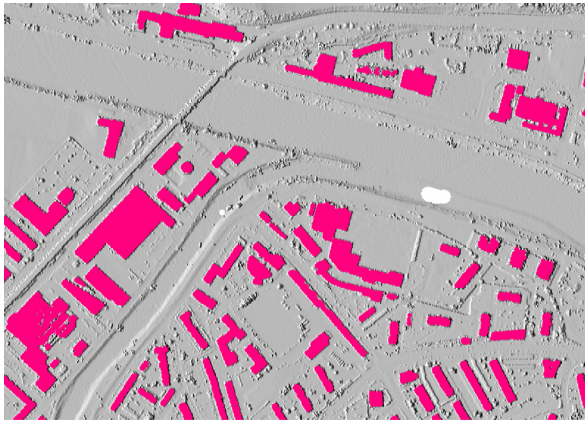

Fig. 6. Classified building footprints from the autumn data set

5.2 Change detection

The comparison of the building footprints from the two epochs is done by a simple overlay of the segments. This leads to an extreme overestimation of changes since also small differences, which occurred from slightly different building outlines in both data sets (i.e. due to differing sensor position in each epoch, registration and rasterization) and uncertainty in the building detection method.

Theses wrongly detected changes are apparent as long and thin segment parts, which can be identified by calculating the shape index. Furthermore, the mean elevation within a segment part must not differ more than 3 m, which ensures that detected changes are equal or larger than the approximate floor height of a building. The overestimation of changes can be enhanced by selecting and relabeling segments parts based on their shape index, height difference between both DSMs, and area.

Fig. 7. Automatically detected locations of changed buildings with two zoomed-in examples from the city centre

The final result of the automatic building footprint change detection is shown in Figure 7. The overall accuracy of detected changes reaches 54%. This comes from a remaining overestimation of detected changes at demolished buildings. The plot in Figure 8 shows all the detected changes labelled by the actual changes derived from the reference. The changes are plotted by their area and height difference. It can be seen that the new and partly new buildings are detected very well reaching an overall accuracy of 90%. The problem arises for demolished and partly demolished buildings where the overall accuracy drops to 32%. This is mainly caused by trees and tree parts wrongly classified as buildings. Further changes not relating to buildings occur at the terrain such as road construction or come from extensive registration errors, which were apparent at the boundary of the test site.

Figure 9 shows the overall accuracy plotted as solid black line for areas from 0 to larger than 500 sqm with a bin size of 50 sqm. The strong influence of changes caused by vegetation for segments smaller than 150 sqm is clearly indicated. If the vegetation removal could be improved, the overall accuracy for the 100 and 150 bin would increase to 100% and 75%, respectively as indicated by the dashed grey line.
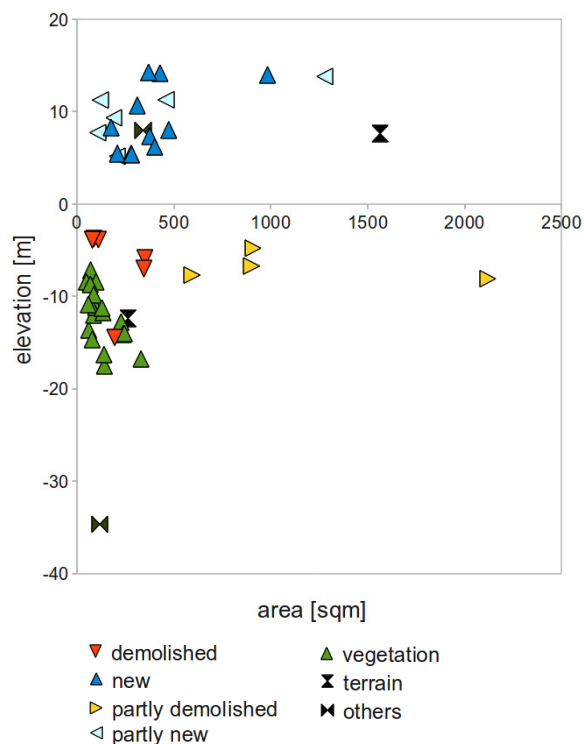
In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents   Author Index   Keyword Index

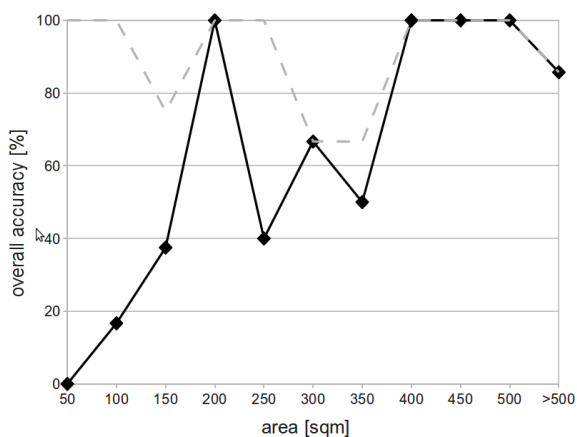Fig 8. Detected changes labelled by reference and clustered by elevation change and area

Fig. 9. Overall accuracy of detected building changes as a function of changed area. The solid line shows the actual accuracy distribution, while the dashed line shows the theoretical accuracy distribution, if vegetation would be classified correctly.

6.   CONCLUSION AND OUTLOOK

The presented study shows that urban areas are highly dynamic environments where major changes on buildings occur also in rather short time intervals (three months). Changes in ALS data appear from several sources such as anthropogenic objects, temporary objects, vegetation, and changes due to data capture conditions and data quality. The assessment of the change detection results shows that the appearance and phenological changes of high vegetation influence the detection success most. If the building detection method tends to misclassify vegetation, care has to be taken to the phenological behaviour of the vegetation between the data acquisition times. One would expect similar good detection results for demolished buildings if a winter and spring data set is compared. Misclassification due to planting of new trees did not occur in the data set. The results show the importance of a reliable vegetation detection procedure in order to be able to monitor changes in urban areas. A more advanced vegetation detection working in the point cloud and making use of full-waveform information might improve the results significantly (e.g. Rutzinger et al., 2008). Future work should focus on the detection and differentiation of building footprints with an area below 100 sqm and height changes below 3 m in order to be able to detect changes on small buildings and to distinguish them from temporary objects. In order to be able to analyse objects in this scale an algorithm working in the point cloud directly might be needed.

REFERENCES

Anegg, J., 2007. *Laserscanning Tirol – Bayern*. Presentation, Federal State of Tyrol, Geoinformation. http://www.interreg-bayaut.net (accessed 2.6.2010)

Arge, L., Chase, J., S., Halpin, P., N., Toma, L., Vitter, J., S., Urban, D., Wickremesinghe, R., 2001. Flow computation on massive grids. In: *Proceedings of the Ninth ACM International Symposium on Advances in Geographic Information Systems*, pp. 82-87.

Breiman, L., Friedman, J., H., Olsen, R., A., Stone, C., J., 1993. *Classification and Regression Trees*. Chapman & Hall, CRC, New York, p. 358

Champion, N., 2007. 2D building change detection from high resolution aerial images and correlation Digital Surface Models. In: *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. XXXVI-3/W49A, pp. 197-202.

Champion, N., Rottensteiner, F., Matikainen, L., Liang, X., Hyyppä, J., Olsen, B., P., 2009. A test of automatic building change detection approaches. In: *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. XXXVIII, Part 3/W4, pp. 145-150.

Durieux, L., Lagabrielle, E., Nelson, A., 2008. A method for monitoring building construction in urban sprawl areas using object-based analysis of Spot 5 images and existing GIS data. *ISPRS Journal of Photogrammetry & Remote Sensing* 63, pp. 399-408

GRASS Development Team, 2010. *GRASS 6.4 Users Manual*. ITC-irst, Trento, Italy. http://grass.itc.it/grass64/manuals/html64_user/ (accessed 2.6.2010)

Maindonald, J., Braun, J., 2007. *Data analysis and graphics using R - An Example-based approach*, second edition. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press. p. 509

In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents   Author Index   Keyword Index

Maktav, D., Erbek, F., S., Juergens, C., 2005. Remote sensing of urban areas. *International Journal of Remote Sensing*, 26(4), pp. 655-659.

Matikainen, L., Hyyppä, J., Ahokas, E., Markelin, L., Kaartinen, H., 2010. Automatic Detection of Buildings and Changes in Buildings for Updating of Maps. *Remote Sensing*, 2(5), pp. 1217-1248.

Matikainen, L., Kaartinen, K., Hyyppä, J., 2007. Classification tree based building detection from laser scanner and aerial image data. In: *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. XXXVI, pp. 280-287.

Murakami, H., Nakagawa, K., Hasegawa, H., Shibata, T., Iwanami, E., 1999. Change detection of buildings using an airborne laser scanner. *ISPRS Journal of Photogrammetry & Remote Sensing*, 54, pp. 148-152.

Olsen, B., Knudsen, T., 2006. Building change detection: a case study comparing results from analog and digital imagery. Technical report, KMS (National Survey and Cadastre) and Danish National Space Centre.

Rehor, M., Baehr, H.-P., Tasha-Kurdi, F., Landes, T., Grussenmayer, P., 2008, Contribution of two plane detection algorithms to recognition of infact and damaged buildings in lidar data. *The Photogrammetric Record*, 23(124), pp. 441-456.

Rottensteiner, F., 2008. Automated updating of building data bases from digital surface models and multi-spectral images: Potential and limitations. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Beijing, China, Vol. XXXVII, Part B3A, pp. 265-270.

Rutzinger, M., Höfle, B., Geist, T., Stötter, J., 2006. Object-based building detection based on airborne laser scanning data within GRASS GIS environment. In: *Proceedings UDMS 2006: Urban Data Management Symposium*, Aalborg, Denmark., digital media.

Rutzinger, M., Höfle, B., Hollaus, M., Pfeifer, N., 2008, Object-Based Point Cloud Analysis of Full-Waveform Airborne Laser Scanning Data for Urban Vegetation Classification. *Sensors*. 8(8), pp. 4505-4528.

Rutzinger, M., Rottensteiner, F., Pfeifer, N. 2009. A comparison of evaluation techniques for building extraction from airborne laser scanning. *IEEE Journal Selected Topics in Applied Earth Observation and. Remote Sensing*. 2(1), pp. 11-20.

Therneau, T., M., Atkinson, E., J., 1997. *An introduction to recursive partitioning using the rpart routines*. Departmnet of Health Science Research, Mayo Clinic, Rochester, MN., technical report 61 edition. http://www.mayo.edu/hsr/techrpt/61.pdf (accessed 2.6.2010)

Vögtle, T., Steinle, E., 2004. Detection and recognition of changes in building geometry derived from multitemporal laserscanning data. In: *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Istanbul, Turkey, Vol. XXXV, Part B2, pp. 428-433.

Vosselman, G., Gorte, B.G.H., Sithole, G., 2004. Change detection for updating medium scale maps using laser altimetry. In: *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Istanbul, Turkey, Vol. XXXV, Part B3, pp. 207-212.

Vu, T., T., Matsuoka, M., Yamazaki, F., 2004. LIDAR-based change detection of buildings in dense urban areas. In: *Proceedings of IGARSS'04*, Anchorage, AK, USA, Vol. 5, pp. 3413-3416.

ACKNOWLEGDEMENTS