HEURISTIC FILTERING AND 3D FEATURE EXTRACTION FROM LIDAR DATA

Abdullatif Alharthy, James Bethel

School of Civil Engineering, Purdue University, 1284 Civil Engineering Building, West Lafayette, IN 47907
alharthy@ecn.purdue.edu, bethel@ecn.purdue.edu

KEY WORDS: LIDAR, feature extraction, building extraction, LIDAR data filtering, tree removal, plane fitting

ABSTRACT:

The need for a fast, efficient and low cost algorithm for extracting 3D features in urban areas is increasing. Consequently, research in feature extraction has intensified. In this paper we present a new technique to reconstruct buildings and other 3D features in urban areas using LIDAR data only. We have tried to show that dense LIDAR (Light detection and ranging) data is very suitable for 3D reconstruction of urban features such as buildings. This concept is based on local statistical interpretations of fitting surfaces over small windows of LIDAR derived points. The consistency of the data with surfaces determines how they will be modeled. Initially, the data has been filtered to remove extraneous objects such as trees and undesired small features. Then, boundaries will be extracted for each facet using statistical information from the surface fitting procedure, and using inferences about the dominant direction. Building features extracted from actual dense LIDAR collected over the Purdue campus are presented in the paper.

1. INTRODUCTION

With the availability of many sources of data such as conventional imagery, SAR imaging, IFSAR DEMs, and LIDAR DEMs, there are many avenues open to derive terrain and feature data in urban areas. Through much research, it has been shown that laser scanning data has the potential to support 3D feature extraction, especially if combined with other types of data such as 2D GIS ground plans (Maas, 1999; Brenner and Haala, 1999; Weidner and Förstner, 1995). Despite the fact that LIDAR data is attractive in terms of cost per high quality data point, the quantity of the data makes a challenge for storage and display (Vosselman, 1999). Acquiring 3D object descriptions from such data is a difficult problem and many approaches have been tried to solve it. Several of them have succeeded with some limitations. The principle idea of this research is to detect and reconstruct buildings form laser altimetry data exclusively.

The building detection procedure described here includes detecting and excluding other natural features such as trees. The type and quality of object description depends on the goal of the research. Our aim is to detect and reconstruct buildings in urban areas. Filtering to identify candidate buildings from other urban features was the first step in this work. Many segmentation techniques such as thresholding determined by histogram analysis, the use 2D GIS data, and multispectral inference have been tested together with LIDAR heights (Mass, 1999; Brunn and Weidner, 1997). Direct thresholding works by extracting the terrain surface using a filtering technique such as the *morphological filter*. Consequently, all objects above the terrain including buildings, trees and others will be detected. This approach should be followed by a refinement step to get the desired results. Using the second strategy, 2D GIS ground maps give the building footprints. However, the LIDAR data gives heights on the building roofs, and roofs can be larger than the ground footprints (in case the footprint represents the building structure rather than the overhanging eaves). Furthermore, most of the roof details are

not shown in the ground plans. The classification based on the multispectral response is limited since it requires the availability of such data, and its accuracy can depend on the complexity of the scene.

In this paper, besides the first and last return analysis, we used the local statistical variation as a key to discriminate buildings from other extraneous objects. Low variation indicates smooth surfaces and, on the other hand, high variation is an indication of inhomogeneous surfaces or, in other words, extraneous objects. Those extraneous objects such as trees have been detected and removed through an iterative procedure. The result of this filtering process is a modified DSM (digital surface model), which represents only terrain and buildings. Moreover, the DEM (digital elevation model) was extracted by applying a region growing segmentation technique to discriminate continuous surfaces from other objects and applying a local minimum filter on other regions. Finally, buildings were detected using the normalized DSM, and their primitive descriptors were extracted. Then, the two dominant directions for each building were computed and its polygon was constructed. A developed shape generalization procedure was applied to the extracted polygons and the 3D model of buildings was constructed. We tested our approach on the data set that has been collected over the Purdue university campus in spring 2001 with an approximate density of one data point per square meter.

2. DATA FILTERING

Laser point clouds should be segmented in order to use them in 3D building reconstruction in urban areas. The segmentation procedure is mandatory to differentiate among diverse objects in the scene. Extraneous objects such as trees, and any other object above the ground that does not belong to the building category should be detected and removed from the scene. The filtering process we used in this project to segment buildings from other undesired objects consists of two steps. The first

one is making use of "first minus last" return analysis and the second step is utilizing the local statistical interpretation. The two techniques are illustrated below in more detail.

2.1 First minus last return height analysis

The LIDAR system, an Optech ALTM 1210 operated by Woolpert Consultants, has the ability to capture two returns (first and last) per each height point. This is due to the fact that the laser pulse is not a single ray but an extended solid angle. It has an angular beamwidth and its footprint will a take circular shape when it reaches the ground. Based on the laser characteristics and the scene characteristics, the laser beam could penetrate some objects. Therefore some of its energy will be reflected back from the object top surface and other portions might penetrate to different depths before they are reflected as shown in figure 1. Generally, this produces an extended return signal. Therefore, the computed height based on the first received return will be called *first return height*. Those heights contain more noise since they reflect every object on the ground such as trees, cars, and buildings as shown in figure 2. On the other hand, the computed height based on the last received return will be called *last return height*. Those heights represent only the non-penetrable objects such as the ground, and buildings as shown in figure 3.   So each derived height point will have two recorded the heights, the first return height and last return height. As a result of that, two different heights of one point give an indication of the presence of a penetrable object such as tree. In contrast, if a data point has the same height for first and last returns, then this point belongs to a non-penetrable object. This step is just to locate the tree regions in the scene by examining the difference between first and last return.
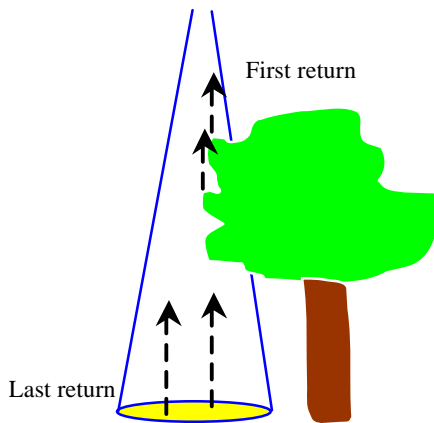

Figure 1. first and last return

The level of the discrepancy between first and last return heights is shown in figure 4a. The discrepancy was larger than zero in the tree regions as expected. However, building boundaries also show a large response. After analyzing the raw data, we found the following explanations for that. When the laser beam hits the exposed surface it will have a footprint with a size in the range of 15-30 cm or more. So, if the laser beam hits the edge of a building then part of the beam footprint will be reflected from the top roof of the building and the other part might reach the ground. In another case, the laser beam might hit the side of a building which results in multiple

returns. The high gradient response on building edges was utilized to filter out the two returns using equation (1) and the procedure is described more in figure 4.

$$
\begin{aligned}
&if \quad gradient \ \geq \ threshold \\
&then \quad (\ first \ - \ last\ ) = 0.0
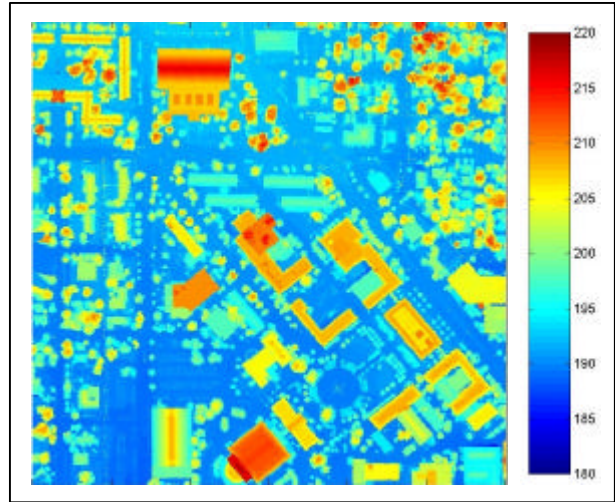\end{aligned} \tag{1}
$$

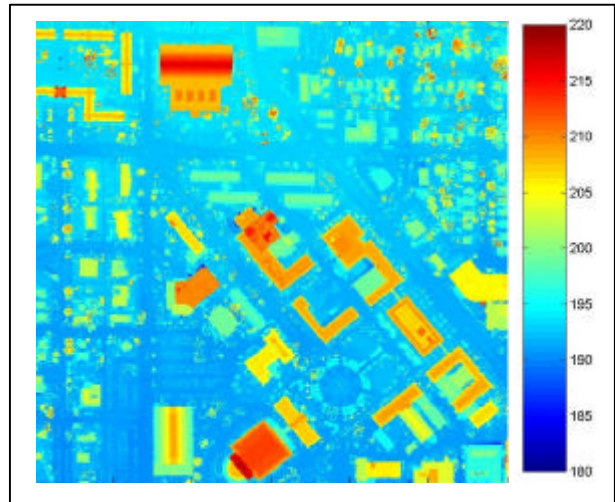Figure 2. color coded map of the last return heights

Figure 3. color coded map of the first return heights

After filtering the discrepancy map, we now conclude that the remaining responses occur only from objects which are not part of a building. So, the first step was to filter the data based on filtered discrepancy responses. The aim here is not to filter the first return height data but to use the discrepancy map to locate the penetrable objects in the last return height data. Consequently, those detected regions will be used to filter the last return data using the local minimum filter. The result of this step was significant since a considerable amount of the noise was removed as shown in figure 5. However, some noise was not cleaned since it represents the center of a dense tree region or its boundaries have a large gradient response. Therefore, a second filtering approach was introduced.
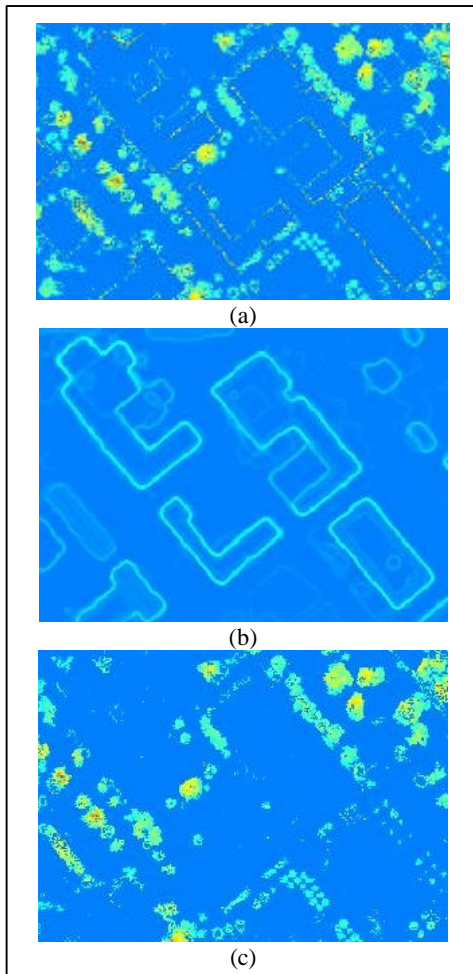
Figure 4. (a) first return height minus last return height (b) gradient based on last return heights (c) filtered discrepancy map between first and last

2.2 Local statistical analysis and interpretation

The surface smoothness was tested through local statistical interpretation. The height variation over a small region is an excellent tool in LIDAR data segmentation (Mass, 1999). Each height group that lies within a small square area will be fit to a plane. The iteratively reweighed least squares adjustment algorithm was used to solve the overdetermined system and obtain the surface parameters (Mikhail, 1976). Weights were assigned to each observation based on its residual, except in the first iteration all observations were weighted equally. After the last iteration in the adjustment procedure, the root mean square error (RMSE) was computed for each square window and recorded at the center of that window.

The number of height points that are included in the surface fitting procedure depends on the window size. For example, if we have a window of 3x3, then the number of observations is equal to nine. Moreover, each of the nine observations is included in the adjustment nine times in nine different windows. Each one of those windows has a different RMSE since it was calculated using different observations. So, the height point might belong to any of the windows that contain this point. The attribute used to classify the point is the RMSE. So, the point will belong to the window that has the minimum RMSE, in order to obtain the best fit to maximize the surface

smoothness. A high RMSE indicates an irregular surface that can be interpreted as a characteristic of a tree or a rough surface, since most buildings have smooth roof surfaces. With a few number of iterations, all high variability surfaces were detected and filtered using a minimum filter with a size equal to the fitting window or larger. The resulting digital surface model (DSM) of the two filtering steps is shown in figure 6.
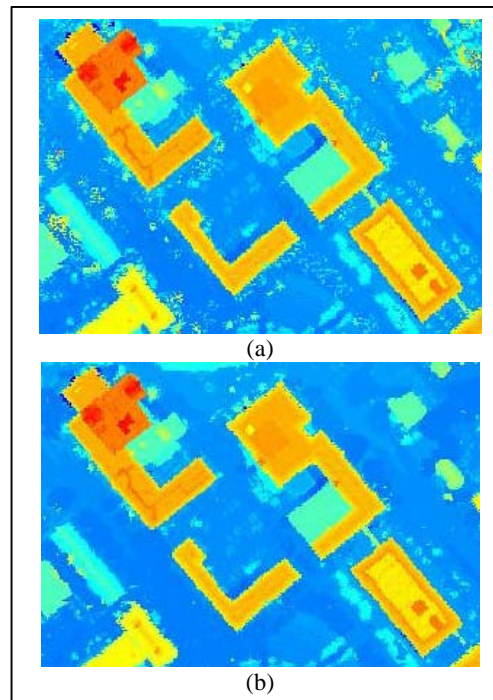

Figure 5.   (a) last return heights before first step filtering, (b) result after first step filtering
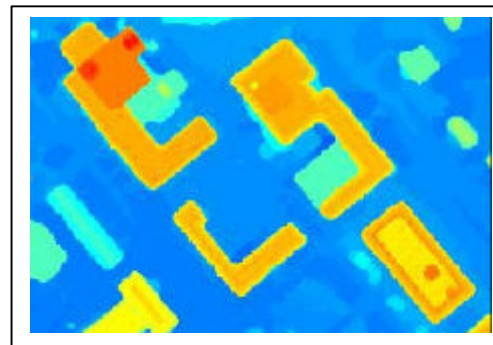

Figure 6. the filtered last return image heights

3. BUILDING FOOTPRINT DETECTION AND DELINEATION

Detecting buildings directly from the raw LIDAR data is not a straightforward problem. This is due to the ambiguity of other vertically extended features which are not buildings in the raw data. Filtering "noise" such as trees and other extraneous objects facilitates the detection of building footprints and consequently the reconstruction procedure. Using the ground plans as in (Brunn and Weidner, 1997) or utilizing a multispectral reflectance for the segmentation as in (Haala and Brenner, 2000) are alternatives to the filtering step to obtain

the building primitives. But since we are trying in this work to test the suitability of the LIDAR data as the only source of information, we decided to extract the building primitives from the LIDAR data after the filtering step.

3.1 Building footprint determination

After removing the extraneous objects from the raw data as described above, the digital elevation model (DEM), which represents the bare ground, was extracted. So, the above ground objects can be obtained by subtracting the DEM from the filtered DSM. However, these non-terrain objects need to be thresholded based on a minimum height and size to remove remaining non-penetrable objects such as cars. The threshold values are chosen based on prior knowledge of building heights and sizes. As shown in figure 7, the resulting building delineations are satisfactory but they need to be converted to regular building polygons. The primitive raster objects can be used to derive vector footprint delineation and connecting those sides under some geometric constraints can create the building polygons.

Figure 7. extracted raster building footprints

3.2 Building polygons

Obtaining reliable and detailed descriptions of urban features remains as the goal of many research efforts. However, the demand for fast and low cost methods for 3D urban feature extraction has limited the level of specific details of those features. Nevertheless, the level of detail is limited also due to some other factors such as the availability of other data sources, the density of the LIDAR data and the complexity of the scene. Therefore, the level of the urban feature detail must be aligned to the purpose of the extraction procedure and the scale of the production.

In this work, we tried not to limit the algorithm by restricting it to a simple building model. However, one constraint was applied to minimize the time duration of this procedure as shown below. We constrained the buildings to have two dominant directions, which are perpendicular to each other. So,

the task now is to convert a building footprint to regular vector building shapes as connected, rectilinear line segments. The steps that were followed in this procedure are shown below:

1. Dominant directions were estimated using image cross-correlation matching. The extracted building footprints images were convolved with a template rotated every two degrees starting from zero to 360. Then the angle attributed to the maximum cross-correlation is recorded as one reading in the angle domain. Therefore, the two peaks in the histogram of angles are estimated as the two dominant directions satisfying the condition that the difference between the two angles is equal to 90 degrees. This step is shown in figure 8.
2. For computational convenience the building footprint was rotated to have horizontal-vertical bearing based on the estimated dominant directions as shown in figure 9b.
3. Then the line segment extraction procedure takes place. The slope of those extracted line segments will be constrained to one of the two estimated dominant directions as shown in figure 9c.
4. Connecting the extracted line segments in order to configure the building polygon as shown in figure 9d.
5. A histogram of the boundary points will be obtained in the two dominant directions in order to generalize the line direction and positions. Boundary points within a limited spacing will be clustered at the maximum as shown in figure 10.
6. The last step is to relocate the building polygon and reregister it again to the data set.
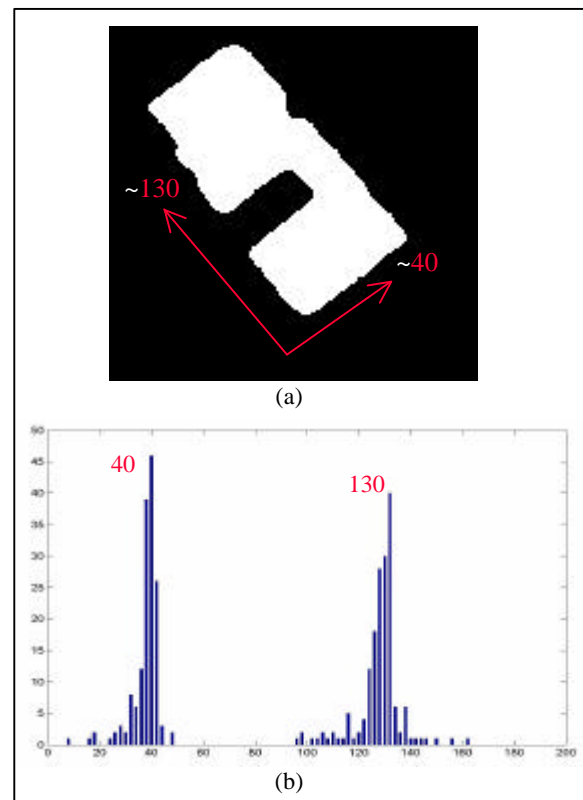

(a)

(b)

Figure 8. (a) building footprint, (b) angle histogram and the estimated dominant directions
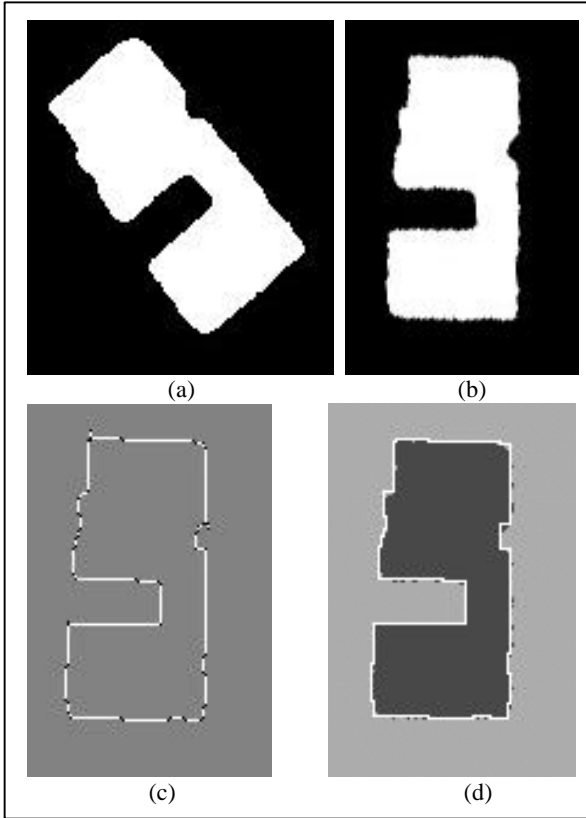
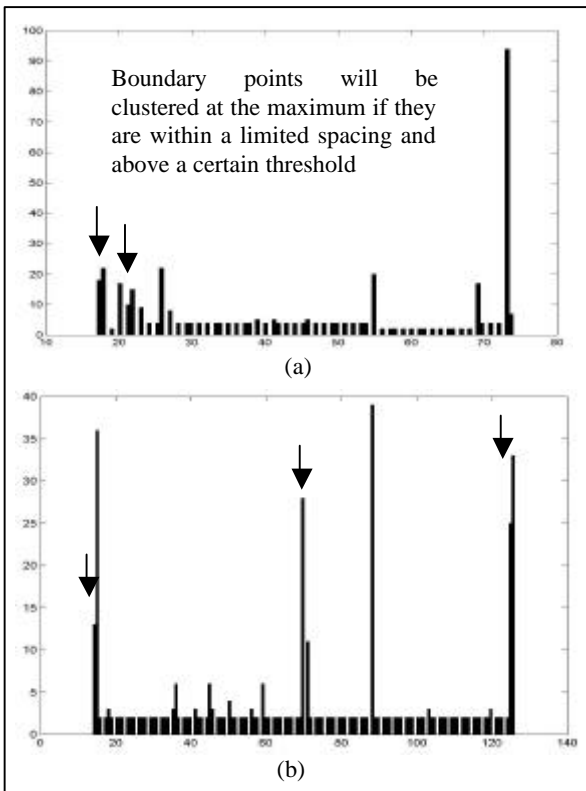Figure 9. (a) building footprint, (b) rotated footprint (c) extracted line segments, (d) extracted polygon

Figure 10. (a) Horizontal coordinates histogram (b) Vertical coordinates histogram

4. DISCUSSION

Our aim in this work is to design a simple and fast method to reconstruct buildings in urban areas using LIDAR data only, which can be useful in many applications. We restricted the procedure to not require any other source of data other than the LIDAR heights. This was done intentionally to avoid the limitation of availability of other sources of information in some areas. Sources such as ground plans, imagery and multispectral data are not available for every desired site. This method consists of some steps starting with filtering the raw LIDAR data to remove "noise" unrelated to buildings. The performance of this step was excellent, however, it is the most time consuming step during the whole procedure. In the building polygon determination we assumed that buildings have only two main directions to facilitate the line segment connection and consequently accelerate the polygon configuration. This method is very useful and effective in reconstructing large areas where buildings have the same dominant directions and it shows satisfactory results when the data was not so dense (one spot height per square meter only). More dense data might improve the extraction procedure, especially the roof details. Figure 11 shows the resulting, generalized, 3D building view as described in the paper.

Rigorous evaluation of these results from photogrammetric building extraction is currently being carried out to assess the quality of the results.
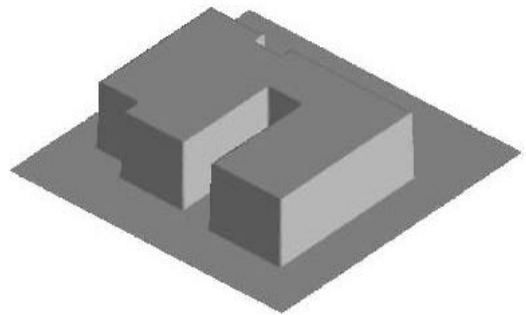

Figure 11. generalized 3D view of the extracted building

REFERENCES

Ackermann, F. 1999. Airborne laser scanning -- present status and future expectations. *ISPRS Journal of Photogrammetry & Remote Sensing,* 54:64-67.

Brenner, C. 2000. Towards fully automated generation of city

models. *ISPRS*, vol. XXXIII, Amsterdam 2000.

Brenner, C., Haala, N. 1999. Extracting of building and trees in urban environments. *ISPRS Journal of photogrammetry & Remote Sensing 54*, 130-137.

Brenner, C., Haala, N. 1999. Rapid production of virtual reality city models. *Geoinformationssysteme*, (2):22-28.

Brunn, A. 2001. Statistical interpretation of dem and image data for building extraction. In A. Grün, editor, *ASCONA*-Workshop 2001. Balkema-Verlag,

Brunn, A., Weidner, U. 1997. Extracting buildings from digital surface models. *IAPRS* Vol. 32, part 3-4w2, stuttgart.

Hug, Ch., Wehr, A. 1997. Detecting and identifying topographic objects in imaging laser altimetry data. *IAPRS* 32, 19-26, part 3-2w3.

Jelalian, A. 1992. *Laser Radar System.* Artech House, Boston.

Mass, G-H. 1999. The potential of height texture measures for the segmentation of airborne laserscanner data. Presented at the 4th *Airborne Remote Sensing Conference and Exhibition*, Ottawa, Ontario, Canada, 21-24 June 1999.

Mass, H., Vosselman, G. 1999. Two algorithms for extracting building model from raw laser altimetry data. *ISPRS Journal of photogrammetry and remote sensing*, 54(2-3):153-163.

Mikhail, Edward M., Ackermann, F., 1976. *Observation and Least Square*. IEP-A Dun-Donnelley Publisher, New York.

Schenk, T., Mcintosh, K., Krupink, A. 2000. Improvement of automated DSM generation over urban areas using airborne laser scanner data. *International Archives of photogrammetry and Remote Sensing*. Vol. XXXIII, part B3. Amsterdam 2000.

Vogtle, T., Steinle, S. 2000. Effective different laser scanning modes on the results of building recognition and reconstruction. *International Archives of Photogrammetry and Remote Sensing*. Vol. XXXIII, part B3. Amsterdam 2000.

Vosselman, G. 1999. Building reconstruction using planar faces in very high density heights data. *IAPRS*, vol. 32, part 3-2w5, 87-92.

Weidner, U., Forstner, W., 1995. Towards automatic building extraction from high resolution digital models. *ISPRS* J. 50 (4), 34-49.