# AUTOMATION OF OBJECT EXTRACTION FROM LIDAR IN URBAN AREAS

*Franz Rottensteiner*

Institute of Photogrammetry and GeoInformation, Leibniz University Hannover,
Nienburger Strasse 1, 30167 Hannover, Germany. E-mail: rottensteiner@ipi.uni-hannover.de

## ABSTRACT

Light Detection and Ranging (LiDAR) has become a valuable data source for urban data acquisition. This paper gives an overview about current trends in the automation of object extraction from LiDAR data. These trends are caused by the technical development of LiDAR sensors that enable the acquisition of point clouds at higher resolution as well as the recording of the full waveform of the returned signal, and by the adoption of processing techniques from the Computer Vision and Pattern Recognition communities. Triggered by these developments, new applications are being found for LiDAR data.

***Index Terms***— LiDAR, urban, automation, extraction

## 1. INTRODUCTION

Light Detection and Ranging (LiDAR) has become a valuable data source for urban data acquisition. Firstly, LiDAR is well-suited for the generation of accurate digital terrain models in urban environments. The explicit height information contained in LiDAR data helps to distinguish elevated objects from the ground. By evaluating this information together with other cues such as surface roughness, intensity, the number of returned pulses or even the full waveform of the returned signal, objects such as buildings and trees can be extracted automatically. The 3D information provided by LiDAR also helps in urban road extraction where image based techniques suffer from problems related to occlusions and poor contrast between roofs and roads. Due to the fact that urban data do already exist in many countries, the automation of change detection has been added to the list of LiDAR applications. This paper gives an overview about the state of the art and current trends in object extraction from LiDAR data with a focus on urban areas. It is restricted to applications of data acquired by airborne LiDAR systems.

## 2. STATE OF THE ART IN AUTOMATED OBJECT EXTRACTION FROM LIDAR

The state of the art in urban object extraction from LiDAR could be summarized as follows [1]. There have been considerable efforts in the automation of the detection and geometrical reconstruction of buildings and roads. It has been shown that these tasks can be automated for extracting the most important structures using first and last pulse LiDAR data of a resolution of about 1 m. There are large-scale tests for the reconstruction of buildings from LiDAR data and existing ground plans, though the level of detail of the reconstructed models is limited by the LiDAR resolution [2]. The planimetric accuracy of the reconstructed buildings or roads is in the order of magnitude of the point spacing. In building extraction, the main problem is that small roof structures may not only lead to a poor resemblance of the model to reality, but that they may lead to a complete failure of the automated approach [3]. In road extraction the major problems are encountered at road crossings, where many model assumptions do not hold [4]. The characterization of trees based on LiDAR has been one of the main topics of research in forestry [5]. In an urban context trees were mainly of interest because they were the object class most likely to be mixed up with buildings and thus had to be considered in the classification process, e.g. [6]. There has also been work on the detection of trees in urban areas [7], though in this context LiDAR was often combined with color infrared (CIR) aerial imagery [8]. Of course, the generation of urban Digital Terrain Models (DTM) is also one of the main applications of LiDAR data, solved by automatic filtering techniques [9]. The major advantages of LiDAR data compared to imagery are the explicit 3D nature of the point cloud and the fact that LiDAR can partly penetrate vegetation. What has hampered progress in automated object extraction so far is the lack of resolution of airborne LiDAR point clouds compared to aerial imagery (at least given the same costs for primary data acquisition) and the lack of spectral content that could be exploited, particularly for the classification of vegetation.

## 3. TRENDS IN AUTOMATED OBJECT EXTRACTION FROM LIDAR

### 3.1. Data Resolution

The first trend to be observed in LiDAR processing is the availability of higher point densities. Typical topographical LiDAR surveys provide point densities of 2-5 points/m$^2$. To a certain degree this has been improved by the development of Multiple Pulses in Air (MPiA) scanners that emit a second pulse before they receive the returned signal of the previous pulse. Using MPiA technology can double the point density at a given flying height or it can double the coverage for a given point density. The advantages of MPiA scanners are limited at very low flying heights, but it would seem that MPiA can considerably reduce the costs for primary data acquisition for urban DTMs [10]. With the high pulse rates of the current laser scanners, point densities of 10-20 points/m$^2$ can easily be obtained from low flying platforms [11], e.g. helicopter-based systems. The point densities can also be improved by acquiring data with multiple overlap [12].

Higher point densities provide a better description of the surface. This improves the prospects of building reconstruction techniques, because smaller roof details can be modeled [13]. As will be pointed out in Section 3.4, very high point densities are a prerequisite for some new applications of LiDAR data because some objects only become visible in LiDAR data of a certain minimum resolution. It has to be noted, though, that higher point densities also may result in problems for common object extraction techniques. Firstly, the memory requirements are increased. Secondly, and more importantly if the point clouds are acquired by multiple-overlap LiDAR strips, mis-registration errors between overlapping strips may affect the outcome of such object extraction techniques. For instance, if registration errors are not considered, the digital surface model (DSM) may appear to be rough on building roofs due to a lateral displacement of the strips, and as a consequence, planar segmentation may fail. This is the reason why prior to object extraction, these mis-registration errors have to be eliminated carefully, e.g. by LiDAR strip adjustment taking into account tie features (mostly planes) in the overlapping areas [12]. Another effect is that 2.5 D algorithms may no longer be suitable for object extraction. Urban areas are characterized by roof overhangs. At the edges of LiDAR strips there are points both on and underneath the roof overhangs, and there are also some reflections on walls. In low resolution data there are relatively few such points, and they are all located at the strip edges. However, with increasing resolution of LiDAR point clouds there will be more such reflections, particularly if the high resolution is caused by multiple overlap: in multiple-overlap data there is a more even distribution of points at strip edges over the entire scene. As a consequence, 3D processing techniques as they are common in terrestrial lasers canning will become more important (cf. Section 3.3).

### 3.2. Full Waveform Processing

Modern LiDAR systems do not only provide one or two points per emitted signal (first and /or last pulse), but they can deliver the full waveform of the received signal [14]. Full waveform data provide challenges in terms of data handling and manipulation. Quite some efforts are spent trying to find appropriate models for decomposing the returned signals, for instance by fitting of Gaussians to the signal [15], which can also be based on statistical sampling [16]. The centers of the fitted Gaussians correspond to objects where a larger portion of the signal is reflected, but in addition, other significant features that are useful for any classification process can be derived, e.g. the pulse width or the signal amplitude [17]. To a certain extent these new features help to overcome the problem of point clouds that there is less information attached to a single point than with digital images. Currently, the focus of full waveform processing is on applications in forestry, where these data can improve the detection and characterization of trees [18]. They are particularly useful in detecting lower forest layers [19]. However, full waveform data can also be used to for urban classification [20]. The separation of trees from buildings and other objects has been a problem for a long time, and new work on characterizing trees might lead to more realistic 3D city models.

### 3.3. Improved Processing Techniques

In order to fully exploit the benefits of the new developments on the sensor side, new processing techniques have to be developed as well. The work on the decomposition and analysis of full waveform data [15], [16], [17] that has already been mentioned in Section 3.2 is one example for this.

There is also a trend to adapt methodology from Pattern Recognition and Computer Vision. This is partly caused by the fact that urban scenes are very complex so that the scene models required for knowledge based object extraction become extremely complex as well. The parameters required for the models may be hard to tune, and the search methods required for scene analysis may become inefficient. A stochastic formulation of the problem and / or a probabilistic classification process based on training data may be a more efficient way to tackle the problem of object recognition [21]. By learning model knowledge from examples in the training phase the methods become more adaptable to varying scenarios and thus more easily transferable. There is a large number of statistical classification methods that have been applied for object extraction from LiDAR data. Maximum margin methods such as *Support Vector Machines* (SVM) try to find a hyperplane in feature space that separates the classes such that the distance of the training point nearest to the decision boundary becomes maximal. SVM were applied to the classification of full waveform data in an urban environment in [17]. *Random Forests* are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest; they have also been used for urban classification of LiDAR data [20]. *Context* can be used as an additional cue for classification. Recently, statistical models of context such as *Conditional Random Fields* (CRF) [21] have thus become increasingly important in image classification. In the context of LiDAR processing CRF have so far only been used for simultaneous classification of terrain vs. off-terrain points and the estimation of heights in a DTM [23], but the principle could be expanded to a classification of the off-terrain points into different object classes. *Statistical sampling* based on marked point processes has been used to delineate buildings from digital elevation models generated by stereo matching or LiDAR [24] with astonishingly good results.

Another important trend is to use real 3D processing. Rather than generating a 2.5D digital surface model that is then analyzed, the points should be used directly for the analysis, and the 3D structure of the scene should be taken into account. This has been standard in terrestrial laser scanning [25], but it has not yet been fully accepted in airborne LiDAR processing mainly due to the fact that the problems caused by a 2.5D approach only becomes critical at high point densities and with multiple overlap data. For example, many of the problems of current algorithms for building reconstruction are related to problems at building outlines, where in overlapping LiDAR strips one might not only get points on the roof, but also on building walls (cf. Section 3.1). A real 3D view on building reconstruction can help to overcome this problem while at the same time pushing the limits of what has been achieved by LiDAR processing so far by extracting the building walls [13] [26].

### 3.4. New Applications

The progress in sensor technology along with new processing techniques has brought about the opportunity to tackle problems that could not be dealt with previously. The extraction of walls in airborne LiDAR data [26] and the characterization of trees in urban areas [17] [20] have already been mentioned. They both can help to improve the generation of 3D city models. In very high-density LiDAR structures that are only separated by a small vertical offset can be differentiated, which has been used for the detection of curbstones [11]. Using this information, the positional accuracy of road edges can be improved.

Today, 3D city models are available in many regions of the developed world. If such a city model is available, LiDAR data from an airborne platform can be matched with the existing model. This can be used for determining the pose and attitude of the aircraft and thus for improved navigation [27]. However, the 3D city model does not only need to be accurate, but it also needs to be up-to-date. Hence, with the availability of urban data increasing all over the world, the problem of change detection [28] or improving the positional accuracy of generalized GIS data [29] will become more and more important.

## 4. CONCLUSIONS

LiDAR has proven to be a technique that is well-suited for urban object extraction. The advantages of LiDAR over aerial imagery are its ability to penetrate vegetation and the fact that it is an active sensor so that there are no problems with natural illumination and shadows. Whereas there is still a lack of spectral information, recent advances in sensor technology have helped to alleviate the problem of a (relatively) low resolution of LiDAR data compared to images. In combination with the use of full waveform data and new processing techniques, this may help to make automated object extraction from LiDAR operational.

## 5. REFERENCES

[1] F. Rottensteiner, “Status and Further Prospects of Object Extraction from Image and LiDAR Data”. *Proc. Joint IEEE-GRSS/ISPRS Workshop on Remote Sensing and Data Fusion over Urban Areas (Urban 2009),* on CD-ROM, Shanghai, China, 20-22 May 2009.

[2] M. Kada and L. McKinley, “3D Building Reconstruction from Lidar Based on a Cell Decomposition Approach”. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W4*, pp. 47-52, Paris, France, 2009.

[3] F. Rottensteiner, “Consistent Estimation of Building Parameters Considering Geometric Regularities by Soft Constraints”. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVI – 3*, Bonn, Germany, 2006.

[4] S. Clode, F. Rottensteiner, P. Kootsookos, and E. Zelniker, “Detection and Vectorisation of Roads from LIDAR Data”. *Photogrammetric Engineering & Remote Sensing* 73(5): 517-536, 2007.

[5] J. Hyyppä, H. Hyyppä, X. Yu, H. Kaartinen, A. Kukko, M. Holopainen, “Forest Inventory Using Small-footprint Airborne LiDAR”. *In: C. Toth, J. Shan (Eds.), Topographic Laser Ranging and Scanning: Principles and Processing,.* Taylor & Francis / CRC Press, Boca Raton, FL (USA), pp. 335-370, 2008.

[6] F. Rottensteiner, J. Trinder, S. Clode, and K. Kubik, “Building detection by fusion of airborne laserscanner data and multi-spectral images: Performance evaluation and sensitivity analysis”. *ISPRS Journal for Photogrammetry and Remote Sensing* 62(2): 135-149, 2007.

[7] M. Rutzinger, B. Höfle, and N. Pfeifer, “Detection of High Urban Vegetation with Airborne Laser Scanning Data”. *Proceedings of ForestSAT07*, 5 p. (on CD-ROM), 2007.

[8] N. Haala and C. Brenner, “Extraction of Buildings and Trees in Urban Environments”. *ISPRS Journal for Photogrammetry and Remote Sensing* 54: 130-137, 1999.

[9] N. Pfeifer, G. Mandlburger, "LiDAR Data Filtering and DTM Generation". *In: C. Toth, J. Shan (Eds.), Topographic Laser Ranging and Scanning: Principles and Processing,* Taylor & Francis / CRC Press, Boca Raton, FL (USA), pp. 307-333, 2008.

[10] R. B. Roth and J. Thompson, "Practial Application of Multiple Pulse in Air (MPiA) LIDAR in Large Area Surveys". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVII – B1*, pp. 183-188, Beijing, China, 2008.

[11] G. Vosselman and L. Zhou, "Detection of Curbstones in Airborne Laser Scanning Data". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W8*, pp. 111-117, Paris, France, 2009.

[12] C. Ressl, G. Mandlburger, and N. Pfeifer, "Investigating Adjustment of Airborne Laser Scanning Strips Without Usage of GNSS/IMU Trajectory Data". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W8*, pp. 195-200, Paris, France, 2009.

[13] P. Dorninger and C. Nothegger, "3D segmentation of unstructured point clouds for building modelling". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVI-3/W49A*, pp. 191-196, Munich, Germany, 2007.

[14] U. Stilla and B. Jutzi, "Waveform analysis for small-footprint pulsed laser systems". *In: C. Toth, J. Shan (Eds.), Topographic Laser Ranging and Scanning: Principles and Processing,* Taylor & Francis / CRC Press, Boca Raton, FL (USA), pp. 215-234, 2008.

[15] W. Wagner, A. Ulrich, V. Ducic, T. Melzer, and N. Studnicka, "Gaussian Decomposition and Calibration of a Novel Small-footprint Full-waveform Digitising Airborne Laser Scanner". *ISPRS Journal for Photogrammetry and Remote Sensing* 60(2): 100-112, 2006.

[16] C. Mallet, F. Lafarge, F. Bretar, M. Roux, U. Soergel, C. Heipke, "A Stochastic Approach for Modelling Airborne LiDARwaveforms". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W8*, pp. 195-200, Paris, France, 2009.

[17] C. Mallet, F. Bretar, and U. Soergel, "Analysis of Full Waveform LIDAR Data for Classification of Urban Areas", *Photogrammetrie Fernerkundung GeoInformation* (PFG) 5: 337–349, 2008.

[18] J. Reitberger, P. Krzystek, and U. Stilla, "Analysis of Full Waveform LIDAR Data for the Classification of Deciduous and Coniferous Trees". *International Journal of Remote Sensing, 25(5)*, pp. 1407-1431, 2008.

[19] J. Reitberger, C. Schnörr, P. Krzystek, and U. Stilla, "3D Segmentation of Single Trees Exploiting Full Waveform LIDAR Data". *ISPRS Journal for Photogrammetry and Remote Sensing* 64(6): 561-574, 2009.

[20] N. Chehata, L. Guo, C. Mallet, "Airborne LiDAR Feature Selection for Urban Classification Using Random Forests". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W8*, pp. 207-211, Paris, France, 2009.

[21] H. Mayer, "Object Extraction in Photogrammetric Computer Vision". *ISPRS Journal for Photogrammetry and Remote Sensing* 63(2): 213-222, 2008.

[22] S. Kumar and M. Hebert, "Discriminative Random Fields", *International Journal of Computer Vision* 68(2): 179–201, 2006.

[23] W.-L. Lu, K.-P. Murphy, J. J. Little, A. Sheffer, H. Fu, "A Hybrid Conditional Random Field for Estimating the Underlying Ground Surface from Airborne Lidar Data". *IEEE Transactions on Geoscience and Remote Sensing* 47(8/2):2913-2922, 2009.

[24] M. Ortner, X. Descombes, and J. Zerubia, "Building Outline Extraction from Digital Elevation Models Using Marked Point Processes". *International Journal of Computer Vision* 72(2):107-132, 2007.

[25] D. Belton, and D. D. Lichti, "Classification and Segmentation of Terrestrial Laser Scanner Point Clouds Using Local Variance Information". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 5*, pp. 44-49, Dresden, Germany, 2006.

[26] M. Rutzinger, S. Oude Elberink, S. Pu, and G. Vosselman, "Automatic Extraction of Vertical Walls from Mobile and Airborne Laser Scanning Data". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W8*, pp. 7-11, Paris, France, 2009.

[27] M. Hebel, M. Arens, and U. Stilla, "Utilization of 3D City Models and Airborne Laser Scanning for Terrain-Based Navigation of Helicopters and UAVs". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W4*, pp. 187-192, Paris, France, 2009.

[28] N. Champion, F. Rottensteiner, L. Matikainen, X. Liang, J. Hyyppä, and B. Olsen, "A Test of Automatic Building Change Detection Approaches". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W4*, pp. 145-150, Paris, France, 2009.

[29] J. Göpfert and F. Rottensteiner, "Adaptation of Roads to ALS Data by means of Network Snakes". *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII – 3/W8*, pp. 24-29, Paris, France, 2009.