A STATE OF ART ON BUILDING FOOTPRINT DERIVATION FROM AIRBORNE LiDAR POINT CLOUDS.

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ABSTRACT

The objective of this paper is to provide the interested reader with a review of LiDAR (Light Detection and Ranging) applications in building footprint derived from airborne LiDAR point clouds and to summarize the current state of the art. LiDAR technology has received great attention due to its ability to accurately measure the shape and height of objects. The advent of LiDAR technique provides resources for building detection. Identify the boundary of the building is necessary for the Cadaster, Real estate industry, Flood management, and Taxation purposes. The extraction of the building boundary is also a crucial and difficult step. At the beginning of this study, a comprehensive overview of the use of LiDAR technology in the building footprint is derived from airborne LiDAR point clouds is discussed. The LiDAR data can be characterized as sub-randomly distributed 3D point clouds which may contain more information than a 2.5D surface model. But, the high amount of noise in LiDAR data and the complexity & diversity of buildings lead to the difficulties in extracting building's boundary. In order to process LiDAR data, expensive hardware is required but, this can be manage with rapid evolution of sensors and high quality data. These LiDAR points have high position accuracy but occlusions and local undersampling may occur. This may result in a lack of significant information for modelling applications. The integration of LiDAR with imaging sensors, efficient using of waveform information and better processing algorithms would make a great development in obtaining more realistic and accurate 3D models of the geospatial objects. Maybe in the future, more cost effective solutions would attract more attention from the users to suite from this technology. Our approaches in this paper are to discuss and propose our observations for future trends and developments towards building footprint derivation from airborne LiDAR points.

1. INTRODUCTION

Buildings, Infrastructure and the Environment are inextricably linked. Energy, Water and Land are all consumed in the construction and operation of Buildings and Infrastructure. These built structures in turn become part of our living environment and affect our living conditions. 3D building models have long been useful in a variety of applications. In these applications, building models are preferred to be composed of several simple parts and organized in a meaningful way. One way to obtain such data is to create building models manually based on Aerial images and other data sources. This solution, however, requires a large amount of manual work, and thus is both slow and expensive. Automatic building detection from high spatial-resolution remote sensing images has gained wide attention for GIS data production, three-dimensional urban visualization, urban infrastructure analysis, and hazard damage evaluation. Many research papers have been published; commercial services and software are available. Brenner (2005), e.g., gives a good overview of reconstruction methods and point out that "research is still far from the goal of the fully automatic reconstruction systems". This situation has not yet changed much, although a lot of research is still devoted to this topic, as can be seen in the multitude of recent publications like Arefi et al., Sohn et al (2008). Therefore it is important to identify and develop sophisticated techniques in order to identify buildings and structures on the ground for the cadastral information, development of infrastructure systems and future developments.

2. CONCEPT OF LIDAR

A LiDAR sensor uses a powerful laser scanner comprised of a transmitter and a receiver, a geodetic quality Global Positioning System (GPS) receiver, and an Inertial Navigation System (INS) unit. The technology resembles that used by radar sensors by which a device emits energy (focused light) and then measures the time it takes to travel to a target and return to a collector and at the same time compensates for the movement of the aircraft and the sensor. Most LiDAR systems use a scanning mirror to generate a swath of light pulses.

The swath width depends on the mirror's angle of oscillation and the ground point density depends on such factors as aircraft speed, system capability for emitting light pulses, and mirror oscillation rate. Ranges are determined by computing the amount of time it takes light to leave its source, travel to the ground, and return to the sensor. The sensing unit's precise position and attitude, instantaneous mirror angle, and the collected ranges are used to calculate 3D positions of terrain points. As many "mass points," as possible can be captured every second. Although features such as buildings and automobiles are included in the accompanying data, these can be removed from Digital Surface Models (DSMs) through post processing filtering techniques. In addition, the ground can be modeled as a "bare-earth" or Digital Terrain Model (DTM).

3. **REVIEW OF CURRENT SITUATION**

Building detection requires high-resolution Aerial photographs or satellite images with resolution higher than 5 meters, which can express buildings as objects instead of mixed pixels Jin, X. and Davis, C.H., (2005). Traditional color or multi-spectral images commonly present shadows and high-rise building displacement problems and make building detection troublesome. Use of satellite images may be affected by cloud and smoke or limited by daylight and low revisit frequency. Also, SAR images have limitations because of considerable noise level associated with the processing and interpretation of complicated images (Eguchi et al., 2010). Therefore many techniques have been developed to detect such data from LiDAR. Point cloud obtained from direct laser scanning of buildings (Li et al., 2008) has the advantage of showing point data but also detailed information like roof and also facade. More research efforts that aim to develop automatic or at least semiautomatic tools for the data acquisition. In general, two kinds of main approaches can be considered to detect, extract and reconstruct buildings from LiDAR data (Hossein, et al., 2013). The first approach is to use only LiDAR data, because the photogrammetry of the region that corresponds to the region of the LiDAR data may be impossible and LiDAR provides more accurate data. The second approach is to use both the LiDAR data and photogrammetric imagery.

3.1 LiDAR Point Segmentation According to Ground or Non-Ground

According to the first category, there have been several attempts to detect building regions from LiDAR data (Awrangjebet al., 2010). The task has been solved by classifying the LiDAR points according to whether they belong to bare earth, buildings, or non-building classes. Therefore in many building extraction approaches, the ground points need to be separated from non-ground points. A number of methods have been developed by Kilian et al., (1996) based on mathematical morphology filters, and a progressive morphological filter was developed to detect non-ground LiDAR measurements. Zhang, K. et al., (2003) improved gradually increasing the window size of the filter and using elevation difference thresholds, the measurements of vehicles, vegetation, and buildings. The result has shown that the filter can remove most of the non-ground points effectively.

Meng X., et al.,(2008), has developed the above method to identify buildings by gradually removing non-building pixels and analytical approach for removing the remaining non-building pixels using size, shape, height, building element structure, and height difference between the first and last return. The results have shown that this method successfully identified most buildings. Few buildings that are smaller than the minimum building threshold are removed from the building candidates. Some larger dense vegetation parcels are troublesome to remove as the vectors present similar size and compactness. This is the disadvantage of this mathematical morphology based method.

Axelsson, P., (1999, 2000) and Vosselman G. (2000) introduced distance-dependent threshold (slope) with a constant size structural element. This modification implies a larger tolerance for more distant points. According to the same approach, Sithole, G. (2001) and Roggero, M. (2001) incorporated the local terrain slope at each point to the structural element definition instead of working with an average slope for the entire area (Vosselman filter). Thus, these new filtering methods have structural elements with constant size but variable form. Kobler, A. et al., (2007) proposed the structural element rotation in order to adapt it to the local slope and, several authors use variable sizes for the structural element, instead of the the fixed sized of the above mentioned methods. For example, Kilian, J. et al., (1996) performs various opening processes with different window sizes. They use the window size as weight in the calculation of the final terrain height. Zhang, K. et al., (2006) proposed a progressive morphological filter based on the progressive morphological filter using a geodetic distance operator.

Regarding object extraction from LiDAR data, it has been defined as a filtering problem of the DSM (raw or interpolated) data by several researchers. All filters make an assumption about the structure of bare earth points in a local neighborhood. Some algorithms used raw data such as: Sohn,G. and Dowman,I., (2002), Roggero, (2001), Vosselman G. and Maas H., (2001), Sithole, (2001), Kraus, K., et al., (1998), while others use interpolated data Elmqvist, M., et al., (2001), Brovelli, M.A., et al., (2002).

Using twelve different datasets, Sithole and Vosselman (2004), made valuable effort to test filter performances on bare earth extraction. All filters perform well in smooth rural landscapes, but all produced errors in complex urban areas and rough terrain with vegetation.

In general, filters that estimate local surfaces were found to perform better. To reduce the errors, authors suggested to use additional data sources, segment-based classification, and self-diagnosis filtering algorithms. Advantages and Disadvantages of Mathematical Morphology based segmentation algorithms are: (a) Most of the non-ground points can be removed effectively. (b) Some larger dense vegetation parcels are troublesome and need to be removed and (c) Produce errors in complex urban areas and rough terrain with vegetation.

3.2 LiDAR Data with Additional Data

The second approach uses both the LiDAR data and photogrammetric imagery. Image and LiDAR datasets have different strengths and weaknesses for object detection. LiDAR data provides 3D coordinates and generally no texture information. Image data has rich spectral information, but that turns into a disadvantage in urban areas because buildings have highly diverse spectral properties. On the other hand, LiDAR data can identify objects using geometric information. The capability of LiDAR data for object detection depends on the used filtering technique. LiDAR data misses some edge points, while image data has a clear advantage on edge features. (Demir, N et al., 2010).

Since LiDAR and photogrammetric imagery have unique advantages and disadvantages for reconstructing building surfaces, advantages of one method can compensate for disadvantages of the other method making it natural to combine the two methods. In general, in order to overcome the limitations of image-based and LiDAR-based techniques, it is of advantage to use a combination of these techniques. In this approach more research has also been done on the extraction of buildings from the (a) combination of Aerial image and LiDAR data (Halla and Brenner, 1999; Rottensteiner and Jansa, 2002; Sohn and Dowman, 2007) and (b) the fusion of LiDAR data and Aerial image (Rottensteiner et al., 2005).

3.2.1 LiDAR Data Combination with Image Data

Combination of Aerial image and LiDAR data; Shan, J. and Sampath, A. (2005), and Demir,N., Baltsavias, E., (2009) many attempts have been made on building extraction from LiDAR points or a digital surface model (DSM) generated from stereo images. In general, the major difficulty in using Aerial images is the complexity and variability of objects and their form, especially in suburban and densely populated urban regions (Weidner, U. and Foerstner, W, 1995). Also the registration of 3D models created from different datasets (El-Hakim et al., 2005) may be a concern. More specifically, intensity and height information in LiDAR data can be used with texture and boundary information in photogrammetric imagery to improve accuracy. Sohn and Dowman (2003) focus on an exploitation of synergy of Ikonos imagery combined with a LiDAR DEM. Specifically, individual buildings are localized with rectangle polygon by a hierarchical segmentation of LiDAR DEM and Ikonos multi-spectral information. However, this method has building extraction errors, such as intrusion/ extrusion of building shape. Sohn and Dowman (2007) presented an approach for automatic extraction of building footprints and the developed technique focuses on an exploitation of synergy of Ikonos imagery combined with a LiDAR DEM.

Vosselman et al., (2004) presented several techniques for segmenting aerial and terrestrial LiDAR points into various classes and extracting different types of surfaces. To a similar level of extent, Brenner, C., (2005) reviews various building reconstruction techniques from images and LiDAR data. Still others (Suveg,I and Vosselman,G., 2004; Fu. C.S., and Shan, J., 2004) use a number of rectangles to approximate and reconstruct the building boundary. In addition, Brunn, A., Weidner, U (1997), Sohn and Dowman (2003), Suveg,I and Vosselman,G (2004) discuss the principle of the minimum description length to determine and regularize the building boundary.

Method based on DSM / DTM comparison in combination with NDVI (Normalized Difference Vegetation Index) Demir, N. and Baltsavias, E. (2010) has analyzed for building detection but here, in the final result, some non-building objects are remaining such as aircrafts and vehicles. The raw DSM data the point density is generally much higher at trees than at open terrain or buildings. Selection window of this approach, a bigger size may result in wrong detection especially in areas where the buildings are neighboring with single trees. The density of point cloud directly affects the quality of the result.

Evaluation results for building extraction based on the nDSM produced using LiDAR DTM. Per-area evaluation method actually means pixel based evaluation, where the raster representation of the detection results and the reference are compared.

Building extraction results are influenced by some errors, e.g. use of Ortho images for vegetation removal, created using photogrammetric DTM where tall objects are not included, slightly miscalculated orientation of some buildings in the area from building outlines and the assumption that all the buildings have rectangular shape.

DTM produced from LiDAR data since the automatically generated DTM from Aerial images contains some errors due to incorrect image matching or inefficient morphological filtering of high objects. Consequently they were not able to detect some smaller buildings from the derived nDSM. Raw LiDAR data has been overlaid on the detection result and later roof surface extraction process has been applied.

The vectorization of buildings by Hough Transform was proposed by several researchers (Cha, J., et al., 2006, Koc San and Turker, 2010). The similar approach employing Radon transform is described in Grigillo D. et al., (2011).

Grigillo D. et al., (2012) has improved above first method and extracted buildings were obtained from nDSM (Normal DSM), generated from LiDAR DSM and photogrammetric DTM. Multispectral images were used to remove vegetation and building outlines were produced using morphologic operations and vectorised using Hough Transform.

As DTM extraction is the most popular and main fundamental process in most of the application, it is always important to seek new accurate and precise methods for DTM production from LiDAR data. There are still some errors in almost all of the DTM calculation approaches which need to be investigated that affect the calculated height of the objects above the terrain surface in the normalized DSM (Mohammadzadeh A. et al., 2008).

Another important observation is that, object based completeness is high when compared to pixel based completeness (Awrangjeb et al., 2010). However, the geometric positional accuracy remains relatively poor for mapping purposes; although not for applications where building detection is the primary goal.

This observation indicates that some of the truly detected buildings are not completely delineated due to small local variations along the roof boundary, occlusion by nearby trees or different roof colours in and out of the initial building position. Consequently, the proposed detection technique can be applied building change detection with high reliability, but it is not as yet applicable to cadastral mapping and accurate roof plane extraction, both of which require higher pixel-based and geometric accuracy.

Recently there was a trend to developed relief displacement correction method. This was to correct for the leaning effect of the buildings Ekhtari, N. et al., (2009) and an object-based classification method to map buildings (Jinfei Wang a,b, 2011), has applied urban building mapping using LiDAR and relief-corrected colour-infrared Aerial images. There are three main stages, (a) Building relief displacement correction in order to map urban tree cover, Lehrbass and Wang (2010) proposed a new method for correcting the cross-track relief displacement in an already orthorectified optical image using LiDAR data. (b) Building extraction using the object-based classification method from the relief-corrected CIR images and the LiDAR derived nDSM and (c) Distinguishing man-made objects from vegetation within the tall object class.

Optical images provide useful information to achieve this task and NDVI is calculated. Kabolizade et al., (2010) presented a building detection method by using image and LiDAR data. In their method, a vegetation index with red and green bands was used for the separation of buildings and trees. A separate tree from buildings, roughness parameter has been used in nDSM data. Most of the buildings have an NDVI value less than 0.1, so use "NDVI<0.1" as the threshold to eliminate vegetation from man-made objects. The above described procedure has been applied to the CIR (Color-infrared) images and LiDAR data that improved result was achieved.

Ahmadi, S. et al., (2010) use the combination of LiDAR data and image and Awrangjeb, et al., (2010), used LiDAR data for building detection and imagery only to remove vegetation, and integration techniques, which use both LiDAR data and imagery as to delineate building outlines. Kabolizade et al., (2010) presented a building detection method by using image and LiDAR data. In their method, a vegetation index with red and green bands was used for separation of buildings and trees. A separate tree from buildings, roughness parameter has been used in nDSM data.

Due to advances in sensor design and data gathering techniques, Aerial photography has been used as a mapping tool for the past years. The knowledge-based image analysis for object extraction and the different aspects of knowledge that can be used for building extraction were reviewed by Eisenbeiss, H .et al (2004). The trends followed within the state of art of building extraction can be found in elsewhere (Baltsavias, et. al., 2001).

Hammoudi and Dornaika (2011) presented a model-based approach for reconstructing 3D polyhedral building models from Aerial images. The 3D polyhedral models estimated directly by optimizing an objective function that is a combination of an image-based dissimilarity measure and a gradient score over several Aerial images.

Each of LiDAR and photogrammetric imagery has particular advantages and disadvantages in horizontal and vertical positioning accuracy in comparison with photogrammetric imagery. LiDAR generally provides more accurate height information but less accurate boundary lines. On the other hand Photogrammetric imagery can provide extensive 2D information such as high-resolution texture, and different indices like NDVI index.

Advantages and Disadvantages of LiDAR data usage with other additional data sources are: (a) Intensity and height information in LiDAR can be used with texture and boundary information in photogrammetric imagery to improve accuracy. (b) LiDAR data for object detection depends on the used filtering technique. LiDAR data misses some edge points, while image data has a clear advantage on edge features. (c) Difficulty in using Aerial images is the complexity and variability of objects and their form, especially in suburban and densely populated urban regions. (d) Aerial images contains some errors due to incorrect image matching or inefficient morphological filtering of high objects. (e) LiDAR generally provides more accurate height information but less accurate boundary lines, and (f) Photogrammetric imagery can provide high-resolution texture, and different indices like NDVI index.

3.2.2 LiDAR Data Fusion with Image Data

The fusion of LiDAR data and Aerial image; Schenk and Csatho (2002) proposed feature-based fusion of LiDAR data and digital Aerial images to obtain a better surface description than could be achieved by using only one of these data sources. The power of fusion of multisource data is that classification accuracy should be improved due to more incorporated features.

Image fusion can be performed at pixel, object or feature, and decision-levels and four different types of ground objects are extracted: Buildings, Trees, Vegetation and Grass (Pohl and van Genderen, 1998; Schistad Solberg et al., 1994) from very-high-resolution images using the feature analyst software.

Feature Analyst provides object extraction classifications by analyzing spatial context in relation to spectral data to classify high-resolution imagery.

Image fusion and subsequent classification can be performed and this fusion is very sensitive to geo-referencing and pixel spacing. Pixel level fusion focused on the merging of physical parameters derived from multisource data.

Object-level image fusion methods usually segment multisource data into meaningful objects. These kind of fusion techniques are often based on the spectra and spatial characteristics derived from datasets and the segmented objects are combined for further object recognition using fuzzy clustering. (Geneletti, D. and Gorte, B.G.H, 2003).

The fusion of Aerial photography and LiDAR data has only been possible in the past few years. Hence combining these common and advance datasets is quite promising for improving land cover mapping (Tao, G., and Yasuoka, Y., 2002). To fuse LiDAR and high-resolution Aerial imagery; Haala and Brenner (1999) combined a LiDAR derived DSM with three-color-band Aerial images to apply unsupervised classification. They used nDSM (normalized Digital Surface Model) and CIR image in their fusion algorithms.

The low-resolution LiDAR data was greatly facilitated to segmentation of trees from buildings by the near-infrared band from the Aerial imagery. Schenk, T. et al., (2002) made them work on the rich properties of LiDAR and Aerial images to extract semantically meaningful information. Rottensteiner et al., (2005) evaluate a method for building detection by the Dempster-Shafer fusion of LiDAR data and multispectral images.

The rule-based classification scheme is applied to building regions, combining NDVI and the average relative heights to separate buildings from other objects. They improved the overall correctness of the results by fusing LiDAR data with multispectral images. Ali S.S et al., (2005) applied an automated object-level technique to fuse high-resolution imagery and LiDAR data.

Hossein, et. al (2013) has introduced an automatic building recognition technique using fusion of LiDAR data and multispectral imagery (Orthorectfied images). Rule-based classification method is considered in order to extract buildings from input data which are DSM, DTM extracted from DSM and an optical Image. To achieve better accuracy, classification of both pixel and object based has been performed. Proposed algorithm successfully detect buildings in urban area. Individual buildings are localized with rectangle polygon by a hierarchical segmentation of LiDAR DEM and Ikonos multi-spectral information.

Sapkota, P., (2008) segments the colored point cloud data which have color information using Hough transform. Recently, LiDAR vendors have begun to make available waveform LiDAR data sets. Waveform data sets contain an entire digitization of the intensity over a brief period for each light pulse. Mallet,C., and Bretar,F., (2009) provided a detailed introduction to such data and the instruments that collect these data.

Wagner et al., (2004) have argued that waveform data already contains sufficient information for target classification. But there are still challenges in data processing, waveform modeling and measurements interpretation of fullwaveform LiDAR. With the availability of full-waveform LiDAR data and hyperspectral imageries, the problems of data fusion and pattern classification become more complicated.

The Rottensteiner et al., (2004) method consists of building detection step, roof plane detection step, and the determination of roof boundaries step. Building detection is based on the Dempster-Shafer theory for data fusion. In roof plane detection, the results of a segmentation of laser scanner data are improved using the digital images.

Advantages and Disadvantages of LiDAR data Fusion with Image Data are: (a) Fusion is very sensitive to georeferencing and pixel spacing. (b) The low-resolution LiDAR data greatly facilitated to segmentation of trees from buildings by the near-infrared band from the Aerial imagery, and (c) Data fusion and pattern classification become more complicated.

4. AUTOMATIC OR SEMI-AUTOMATIC BUILDING EXTRACTION APPROACH

A number of problems with building detection have been discussed in the literature. Data from laser scanner are still expensive or inexistent (Alobeid et al., 2010). Elberink et al., (2011) mentioned that in a raw laser point cloud systematic and stochastic errors occur which depend on the configuration during the time of acquisition. Weidner and Förstner (1995), Ekhtari,N et al (2008) use the difference between DSM and DTM to determine the building outlines. Brunn,A and Weidner,U., (1997) has mentioned building detection and reconstruction using parametric and prismatic building models and shows automatic procedures may fail in recovering the correct information due to the complexity of the task.

Wang,Z., and Schenk,T., (2000) generated the triangulated irregular network (TIN) model from the LiDAR points. Triangles are then grouped based on the orientation position to form larger planar segments. The intersection of such planar segments results in building corners or edges. Few commercial software packages allow automatic terrain, tree and building extraction from LiDAR data. Wang,Z., and Schenk,T., (2000), Morgan and Habib (2002) determined the break-lines in a raw LiDAR dataset and form the TIN model. Through a connected component analysis on the TIN model individual buildings are segmented.

Based on a cell decomposition approach, Kadaa, M. et al., (2009) has introduced and produced LOD2 models from existing ground plans and LiDAR data. As well-formed roof structures are of high priority and developed an approach that constructs models by assembling building blocks from a library of parameterized standard shapes.

LiDAR has offered a favorable option for improving the level of automation in building detection process when compared to image-based detection (Vu et al., 2009). A semi-automatic approach is proposed for the extraction of closed polygon footprints by Shirowzhan S, (2010). Two types of closed polygons have been investigated and it has reliable results because the closed polygon footprints can be extracted with a high Kappa Index. For the closed buildings, the closed polygons were transformed to simple open polygons and extracted automatically.

Biggest issues were when the closed polygons are extracted without detection of the hole inside the polygon and when the procedure changes to extracting the simple shape footprints. Then two types of errors have occurred, (a) gap area for the closed polygon and some errors for uncovered areas; and (b) convexity in the straight lines. The footprint generalization or fuzzification approach would be the common solution for this.

As mentioned above, many researches have proposed different methods for detection and extraction of buildings from LiDAR data or combination of both high resolution Aerial images and LiDAR data. Among those researchers, very few have gone through an automatic extraction and reconstruction of buildings in 3D space. Kabolizade et al (2012), proposed a method based on Genetic Algorithms (GA) to find optimized height and slopes of gable roof in building models. The mentioned algorithm consists of three steps; (a) building boundaries are detected (b) initial building contours are generalized and buildings are extracted and (c). GA based method has used for reconstructing the building models. This approach has proved that it is computationally efficient and has acceptable accuracy.

Lack of quantitative error analysis is a common problem in this area. Hence, it may be necessary to investigate approaches for measuring the error of reconstructing results without ground truth. LiDAR data is normally a huge data set containing several millions of points, it is a common solution to divide the initial data set into several different pieces, each of which could be loaded into memory and processed at a time.

Wang, O. et al (2006), has shown a bayesian approach to building footprint extraction and automatically constructing building footprints from a pre classified LiDAR point cloud. Here, algorithm first computes a bounded error approximate building footprint using an application of the shortest path algorithm and then determine the most probable building footprint by maximizing the posterior probability using linear optimization and simulated annealing techniques. A number of problems with building detection have been discussed in the literature (Elberink et al., 2011). Lafarge et al. (2008) presented an automatic building extraction method that involved DEMs based on an object approach. By using this method, a rough approximation of all relevant building footprints were first calculated from marked point processes.

To improve the accuracy of the final output researchers have used orientation and shape of buildings. In fact, a rectangle is fitted to each of the buildings and then the orientations of these rectangles represent orientations of the buildings. These types of methods lead to better performance due to the orientation information obtained from the buildings. Gerke et al., (2001) used a recursive cut of rectangles from a minimum enclosing rectangle in order to fit a rectangular outline. A similar approach was introduced by Dutter et al. (2007) which started with a Minimum Bounding Rectangle (MBR) and determined relevant deviations from the rectangle lines. Shan and Sampath (2007) used straight lines in the main direction of the buildings to approximate the shape. Basically, two reconstruction methods can be considered (**a**) The model based method and, (**b**) Data driven methods (Kabolizade et al. 2010).

From Airborne Laser Scanner (ALS) points has been used by, Kada and McKinley (2009), Sampath and Shan (2010) and presented solutions for the segmentation and reconstruction of polyhedral building roofs in data driven method. In the data driven methods, the roof building is partitioned to flat surfaces and a plan is fitted to each flat surface. Kim and Shan (2011) presented a novel approach for building roof modeling from ALS data. Segmentation was performed by minimizing an energy function which formulated as multiphase level set. To reconstruct a 3D roof model, roof structure points were determined by intersecting adjacent roof segments or line segments of buildings.

In the data driven methods, the performance of methods depends on the clustering method and selected thresholds by an operator. The over- and under-segmentation is the most important drawback of these methods that affect the reconstruction result. Another limitation of these methods is to determine the topologic relations among the detected roof segments (Forlani et al., 2006).

On the other hand, in these methods the library of simple models are not required and these methods are more flexible. The methods those belong to the second category are model based. These types of methods are limited by the complexity of roof shapes, since the possibility to form complex roofs is limited to the set of available primitives. Reconstruction of complicated building in the model based methods, model is carried out by use of some predefined simple primitives. Lafarge et al., (2006) applied simple rectangle primitives placed by a DTM. Lafarge et al. (2008) presented a new approach for building reconstruction from a single DEM and treated buildings as an assemblage of simple urban structures extracted from a library of 3D parametric blocks.

According to Forlani et al., (2006), Oude Elberink and Vosselman (2009), Sampath and Shan (2010), Verma et al., (2006), the advantage of model-based approaches is that it can always reconstruct a topologically consistent model. On the other hand, one of the important deficiencies of model based reconstruction methods is their dependencies to predefined simple models. The model based reconstruction approach based on genetic algorithm that has no dependency to predefined model.

Kabolizade, k. et al., (2012) proposed algorithm for reconstruction, buildings are extracted and reconstructed from DSM generated by ALS data. The ALS can acquire a high density of laser points to generate the DSM of a urban area. The proposed method can reconstruct complex building roofs using a flexible model that has no need to predefined simple primitives.

Converting data from irregular 3D point clouds to other models usually leads to information loss; and the high computation cost of converting a large volume of point data is a considerable problem for any large scale LiDAR applications. Sampath, A. and Shan, (2007) has introduced building boundary tracing and regularization from raw LiDAR points and it consists of four sequential steps: (i) points are separated to ground and non-ground; (ii) Moving window used to segment individual buildings. (iii) A modified convex hull formation algorithm is applied to find the building boundary points and (iv) Regularize the building boundary. The modified convex hull algorithm has effectively traced the boundary points and forms the initial good approximation of the building boundary.

Advantages and Disadvantages of Automatic or Semi-automatic building extraction methods are: (a) More fast extraction for low density area. (b) Closed polygon footprints can be extracted with a high Kappa Index. (c) Difficult to separate the closed polygons with inside the hole. (d) Discrimination between trees and buildings is almost impossible. (e) Gap area for the closed polygon and some errors for uncovered areas; and convexity in the straight lines, and (f) Accuracy depends on the assumptions of the model.

5. FUTURE TRENDS

Automated processing and exploitation of LiDAR and imagery data is important (Olsson, H, 2003) because LiDAR sensors are now almost always bundled with digital cameras onboard. The co-registration of pixel information with LiDAR point clouds provides increased visualization at very-high spatial resolutions, with 5 -25 cm vertical and 5-40 cm horizontal accuracy, as well as improved accuracy in object detection and extraction especially in high density urban environments. According to the analysis and future trends, current developments in the integration of multiple digital data sets are generating 3D geospatial information that, previously, has been unattainable.

Ackermann, F.,(1999) has analyzed the concept of data fusion can be pushed very much further, Fusion of geospatial data from different sources allows the creation of thematic data layers and structural features for urban and natural environments. Fusion of geospatial data from different sources is Spectrum Mapping; Spectrum (Spectrum's full-service mapping core competencies are in the fields of Photogrammetry; Remote Sensing Services that include LiDAR) developed a process to fuse data from various sensors such as LiDAR, hyper-spectral, and multi-spectral digital cameras to create "Intelligent Data".

Sensors based on current LiDAR instruments may suffer from a limited number of multiple returns and poor range estimation. Additionally, there is little information about the characteristics of the illuminated surface. However, latest generation full-waveform LiDAR systems are able to record the entire waveform of each received laser pulse. The challenge is to use this waveform data to create more accurate and reliable target images (Toth, C, 2010). Future research will be more likely about analyzing additional features extracted from the waveform and establishing neighborhood relationships between successive echoes to classify urban scenes (fine detection of edges of roofs, exact separation between vegetation and buildings)(Mallet, C.,2009). Recent work has developed a new waveform decomposition approach, the challenge is to implement full-waveform processing in real time and assess the increase in precision of target detection. A further challenge is to investigate the use of waveform derived information such as pulse width and backscatter cross-section to extract potential target information.

6. CONCLUSION

In this review paper, several methods and application procedures from previous research in building footprint detection, extraction and reconstructions on LiDAR point clouds have been discussed. Some results depend on the application algorithms and some depend on the density of the point cloud (Urban or non-urban).

Considering all published papers we identify building footprint extraction as all of those approaches, which belongs to the (a) 2D building boundary extraction describing the outlines of the building from LiDAR point cloud or fusion of LiDAR data with other data sources (Ivan. T. et al., 2015), (b) 3D model reconstruction based on the LiDAR data only or fusion of LiDAR data with other data sources, or (c) Identifying object height from generated TIN, DEM or DSM and classifying building boundaries, roof boundaries from LiDAR data or fusion of LiDAR data with other data sources.

Most of the research results achieved by the methods for building detection have shown that this task can be satisfactorily solved for buildings by methods relying on different processing strategies and different sensor data, but there is still discussion for improvement in detecting small building structures and imprecise delineation of the building boundaries. Most of the methods for tree detection were successful in detecting large trees under favorable conditions, but failed to do so in very complex inner city environments.

Small trees could not be detected reliably by any of the methods, either; this seems to indicate a field requiring further research. The results achieved for 3D building reconstruction showed the potential, but also the limitations of state of the art methods.

All the research papers discussed above have shown that following tasks to be achieved to success in more accurate building footprint extraction from LiDAR point clouds in future.

- (a) Completely automated method for 2D or 3D building boundary extraction.
- (b) LiDAR data filtering and classification, which requires efficient data processing software. However, it is not only software missing at this point, but algorithms.
- (c) High quality reference data sets for accuracy assessment.
- (d) Introduce of low cost light weight LiDAR sensor system compatible to UAV and
- (e) Integration with other sensors in order to increase the resolution of the data.

LiDAR data is still complicated to work with due to its size, but can be managed entirely through open source tools. Advances in LiDAR technology are making LiDAR data more available. Understanding vertical growth of urban area is as important as understanding its horizontal growth. Building boundary and heights are crucial data for disaster management, cadastral information and local administration purposes.

Please consider that the above discussed issues are authors' personal point of view.

REFERENCE

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

Ahmadi, S M.J.V. Zoej, H. Ebadi, H.A. Moghaddam, and A.Mohammadzadeh, (2010): Automatic urban building boundary extraction from high resolution Aerial images using an International Journal of Applied Earth Observation and Geoinformation, Vol. 12, No. 3, pp. 150-157, 2010.

Ali, S., S., Dare, P., Jones, S., 2005. Automatic classification of land cover features with high resolution imagery and LiDAR data: an object-oriented approach. In: SSC 2005 Spatial Intelligence, Innovation and Praxis: The national biennial Conference of the Spatial Sciences Institute. Melbourne, Australia, pp. 512–522.

Alobeid, A., Jacobsen, K., & Heipke, C. (2010). Comparison of Matching Algorithms for DSM Generation in Urban Areas from Ikonos Imagery. Photogrammetric Engineering and Remote Sensing, 76(9), 1041-1050.

Ardila Lopez, J.P., Tolpekin, V.A., Bijker, W. and Stein, A. (2011): Markov - random - field - based super - resolution mapping for identification of urban trees in VHR images. In: ISPRS Journal of Photogrammetry and Remote Sensing, 66 (2011)6 pp. 762-775.

Arefi, H., Engels, J., Hahn, M. and Mayer, H., (2008): Levels of Detail in 3D Building Reconstruction from LiDAR Data. International Archives of the Photogrammetry, RS and Spatial Information Sciences, Vol. 37, pp. 485–490.

Arefi, H. and Hahn, M., (2005): A morphological reconstruction algorithm for separating off-terrain points from terrain points in laser scanning data. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. 36 (3/W19).

Awrangjeb, M., Ravanbakhsh, M., Fraser, C. S., (2010): Automatic building detection using LiDAR data and multispectral imagery In Digital Image Computing Techniques and Applications, Sydney, Australia, pp. 45-51.

Axelsson, P., (1999): Processing of laser scanner data- Algorithms and applications, ISPRS Journal of Photogrammetry and Remote Sensing, 54(2–3):138–147.

Axelsson, P., (2000): DEM generation from laser scanner data using adaptive TIN models. International Archives of the Photogrammetry and Remote Sensing, XXXIII Part B4/1, 110-117.

Baltsavias, E. P., Gruen, A., and Van Gool, L., (2001b): Automatic Extraction of Man-Made Objects from Aerial and Space Images (III), Lisse, The Netherlands, Balkema.

Brunn, A., Weidner, U., (1997): Extracting Buildings from Digital Surface Models. IAPRS 32 (3-4W2), pp. 27-34.

Brenner, C., (2005): Building reconstruction from images and laser scanning, International Journal of Applied Earth Observation and Geoinformation, Vol. 6, pp. 187–198.

Brovelli, M.A., Cannata, M., Longoni U.M., (2002): Managing and processing Lidar data within GRASS. Proc. of the GRASS Users Conf. 2002, Trento, Italy.

Brunn, A., Weidner U., (1997): Extracting Buildings from Digital Surface Models. IAPRS 32 (3-4W2), pp. 27-34.

Cha, J., Cofer, R. H., Kozaitis, S. P., (2006): Extended Hough Transform for linear feature detection. Pattern Recognition, 39, pp. 1034-1043.

Demir, N and E. Baltsavias, (2010): Automated modeling of 3D building roofs using image and LiDAR data, ISPRS Commission IV, WG IV/2.

Demir, N., Baltsavias, E. (2009): Extraction of buildings using images & LiDAR data and a combination of various methods, International Archives of the Photogrammetry, RS and Spatial Information Sciences, vol. 38, p. W4.

Demir, N., Baltsavias, E., (2010): Combination of Image and LiDAR Data for Building and tree Extraction. IAPRS, Vol. XXXVIII, Part 3B, Saint-Mandé, France.

Dutter, M., 2007: Generalization of building footprints derived from high resolution remote sensing data, Diploma Thesis TU Vienna, 2007.

Eguchi, R., Huyck, C., Ghosh, S., Adams, B., & McMillan, A. (2010). Utilizing New Technologies in Managing Hazards and Disasters. In P. S. Showalter & Y. Lu (Eds.), Geospatial Techniques in Urban Hazard and Disaster Analysis (Vol. 2, pp. 295-323): Springer, Netherlands.

Elberink and George Vosselman, (2011): Quality analysis on 3D building models reconstructed from airborne laser, scanning data, ISPRS Journal of Photogrammetry and Remote Sensing 66 (2011) 157–165.

El-Hakim, S., Whiting, E., Gonzo, L., & Girardi, S. (2005). 3D Reconstruction of Complex Architectures from Multiple Data.

Eisenbeiss, H., Baltsavias, E., Pateraki, M. and Zhang, L., (2004): Potential of IKONOS and Quick Bird imagery for accurate 3D point positioning, orthoimage and DSM generation. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35(B3): 522–528.

Ekhtari, N., M. R. Sahebi, M. J. Valadan Zoej, and A. Mohammadzadeh, (2008): Automatic building detection from LiDAR point cloud data, 21st ISPRS Congress, Commission, WG IV/3, Beijing, China, 2008.

Ekhtari,N., Mohammad Javad Valadan Zoej, Mahmod Reza Sahebi, and Ali Mohammadzadeh., (2009): Automatic building extraction from LiDAR digital elevation models and WorldView imagery. Journal of Applied Remote Sensing, Vol. 3.

Elmqvist, M., Jungert, E., Lantz, F., Persson, Å. and Söderman, U., (2001): Terrain modeling and analysis using laser scanner data. International Archives of Photogrammetry and Remote Sensing and Spatial Information Sciences, XXXIV-3/W4, 219- 226.

Forlani, G., Nardinocchi, C., Scaioni, M., Zingaretti, P., 2006.Completeclassification of raw LiDAR data and 3D reconstruction of buildings. Pattern Analysis & Applications8 (4), 357–374.

Fu. C.S., and J. Shan, (2004): 3-D Building Reconstruction from Unstructured Distinct Points, Int. Archives Photogrammetry Remote Sens., vol. 35, part B3, CD-ROM, 2004.

Geneletti, D., Gorte, B. G. H., (2003): A method for object-oriented land cover classification combining Landsat TM data and Aerial photographs. International Journal of Remote Sensing, 24(6): 1273–1286.

Gerke M, Heipke C, Straub BM (2001) Building extraction from Aerial imagery using a generic scene model and invariant geometric moments. In: Proceedings of the IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion over Urban Areas, 8-9 November 2001, University of Pavia, Rome, Italy, pp 85-89.

Grigillo D., Kanjir. U., (2012): Urban Objects Extraction From Digital Surface Model and Digital Aerial Images. ISPRS Journal of Photogrammetry and Remote Sensing and Spatial Information Sciences, Vol 1-3, pp.215-220.

Grigillo, D., Kosmatin Fras, M., Petrovič, D., (2011): Automatic extraction and building change detection from digital surface model and multispectral orthophoto. Geodetski vestnik 55: 28-45.

Haala, N. and Brenner, C., (1999): Virtual city models from laser altimeter and 2D map data. Photogrammetric Engineering and Remote Sensing, 65(79), pp. 787-795.

Hammoudi, K., Dornaika, F., 2011. A featureless approach to 3D polyhedral building modeling from Aerial images. Sensors11, 228–259.

Hossein, Arefi, Amin, Alizadeh, Ali, Ghafouri, (2013): Building Extraction using Surface model Classification, GIS Ostrava 2013 - Geoinformatics for City Transformation January 21 – 23, 2013, Ostrava.

Ivan T., B Höfle, D Tiede, T Blaschke (2015), Building Extraction from Airborne Laser Scanning Data: An Analysis of the State of the Art Remote Sensing 7 (4), 3826-3862.

Jinfei Wanga, B, Lehrbassb B, and Chuiqing Zenga, B, (2011): Urban Building Mapping using LiDAR and Relief-Corrected Colour-Infrared Aerial Images. State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, China.

Jin, X., and C.H. Davis, (2005): Automated building extraction from high-resolution satellite imagery in urban areas using structural, contextual, and spectral information, EURASIP Journal on Applied Signal Processing, 2005(14):2196–2206.

Kabolizade, M.; Ebadi, H.; Ahmadi, S. An improved snake model for automatic extraction of buildings from urban aerial images and LiDAR data. Comput. Environ. Urban Syst. 2010, 34, 435–441.

Kabolizade., M., Hamid Ebadi, Ali Mohammadzadeh, (2012): Design and implementation of an algorithm for automatic 3D reconstruction of building models using genetic algorithm. International Journal of Applied Earth Observation and Geoinformation, 19 (2012) 104–114.

Kadaa M. and McKinleyb L., (2009): 3D Building Reconstruction from LiDAR based on a cell decomposition approach, IAPRS, Vol. XXXVIII, Part 3/W4 Paris, France, 3-4 September.

Kilian, J., N. Haala, and M. English, (1996): Capture and evaluation of airborne laser scanner data, International Archives of Photogrammetry and Remote Sensing, Vol. XXXI, Part B3, pp. 383–388.

Kim, K.; Shan, J. Building roof modeling from airborne laser scanning data based on level set approach. ISPRS J. Photogramm. Remote Sens. 2011, 66, 484–497.

Kobler, A., Pfeifer, N., Ogrinc, P., Todorovski, L., Ostir, K. and Dzeroski, S., (2007): Repetitive interpolation: A robust algorithm for DTM generation from aerial laser scanner data in forested terrain. Remote Sensing of Environment, 108(1), 9-23.

Koc San, D., Turker, M., (2010): Building extraction from high resolution satellite images using Hough transform. The International Archives of Photogrammetry, Remote Sensing and Spatial Science 2010, 38 (8), pp. 1063-1068.

Kraus, K. and Pfeifer, N., (1998): Derivation of digital terrain models in wooded areas with airborne laser data. ISPRS Journal of Photogrammetry and Remote Sensing, 53(4), 193-203.

Lafarge, F., Descombes, X., Zerubia, J., Pierrot-Deseilligny, M., 2008. Automatic building extraction from DEMs using an object approach and application to the 3D-city modeling. ISPRS Journal of Photogrammetry & Remote Sensing 63, 365–381.

Lafarge, F., Descombes, X., Zerubia, J., and Deseilligny, M., 2006a. An automatic 3D city model: a Bayesian approach using satellite images. InProc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Toulouse, France.

Li, M., Cheng, L., Gong, J., Liu, Y., Chen, Z., Li, F., Song, X. (2008). Post-earthquake assessment of building damage degree using LiDAR data and imagery. Science in China Series E-Technological Sciences, 51, 133-143.

Lohmann, P., Koch, A. and Schaeffer, M., (2000): Approach to the filtering of laser scanner data. International Archives of Photogrammetry and Remote Sensing, XXXIII, Part B3/1, 534-541.

Mallet, C., Frédéric Bretar., (2009): Full-waveform topographic LiDAR: State-of-the-art, ISPRS Journal of Photogrammetry and Remote Sensing 64 (2009) 1-16.

Meng X. and Wang L., (2008): Morphology based building detection from Airborne LiDAR Data, ASPRS 2008 Annual Conference, Portland, Oregon, April 28 – May 2.

Mohammadzadeh A. and M. J. Valadan Zoej., (2008): A Sate of Art on Airborne LiDAR Application In Hydrology and Oceanography: A Comprehensive Overview, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B1. Beijing 2008.

Morgan, M., and A. Habib, (2002): Interpolation of LiDAR data and automatic building extraction, ACSM-ASPRS Annual Conference Proceedings.

Olsson H., (2003): Summary of the Scand Laser 2003 workshops and recent developments in Sweden, Department of Forest Resource .Management and Geomatics, Swedish University of Agricultural Sciences, Umeå, Sweden.

Oude Elberink, S., 2009. Target graph matching for building reconstruction. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 38 (Part3/W8), 49–54.

Persson, Å. J. Holmgren, and U. Södermann., (2002): Detecting and measuring individual trees using an airborne laser scanner, Photogrammetric Engineering & Remote Sensing, 68(9):925–932.

Pohl, C., van-Genderen, J. L., (1998): Multisensor image fusion in remote sensing: concepts, methods and applications. International Journal of Remote Sensing, 19(5): 823–854.

Roggero Marco., (2001): Airborne laser scanning: clustering in raw data, International Archives of Photogrammetry, Remote Sensing, 34, 227–232.

Rottensteiner, F., and. Briese C., (2002): A new method for building extraction in urban areas from high-resolution LiDAR data, Proceedings of the ISPRS Commission III Symposium, Graz, Austria.

Rottensteiner, F., Trinder, J., Clode, S., and Kubik, K., 2004. Using the Dempster Shafer method for the fusion of LiDAR data and multi-spectral images for building detection. Information Fusion.

Rottensteiner, F., Trinder, J., Clode, S. and Kubik, K., (2005): Using the Dempster-Shafer method for the fusion of LiDAR data and multi-spectral images for building detection. Information Fusion, 6(4), pp. 283-300.

Sampath, A. and Shan J., (2007): Building Boundary Tracing and Regularization from Airborne LiDAR point Clouds, Photogrammetric Engineering & Remote Sensing, Vol. 73, No. 7, pp. 805–812.

Sampath, A., Shan, J., 2010. Segmentation and reconstruction of polyhedral building roofs from aerial LiDAR point clouds. IEEE Transactions on Geoscience and Remote Sensing 48, 1554-1567.

Sapkota, P., (2008): Segmentation of Colored Point Cloud Data. MSc Thesis, ITC. Enchede, The Netherlands.

Schenk, T., Csatho, B., 2002. Fusion of LiDAR data and aerial imagery for a more complete surface description. International Archives of Photogrammetry & Remote Sensing and Spatial Information Sci. 34 (Part 3), 310–317.

Schistad-Solberg, A., H., Jain, A., K., Taxt, T., (1994): Multisource classification of remotely sensed data: fusion of Landsat TM and SAR image. IEEE Transactions on Geosciene and Remote Sensing, 32(4): 768–778.

Shan, J., and A. Sampath, (2005): Urban DEM generation from raw LiDAR data: A labeling algorithm and its performance, Photogrammetric Engineering & Remote Sensing, 71(2):217–226.

Shirowzhan S. and Lim S., (2010): Extraction of Polygon Footprints from LiDAR Data in Urban Environment. School of Surveying and Spatial Information Systems, UNSW, Sydney, NSW 2052, Australia.

Sithole, G., (2001): Filtering of laser altimetry data using a slope adaptive filter. IAPRS, Vol. 34, Part 3, pp. 203-210.

Sithole, G., and G. Vosselman, (2004): Experimental comparison of filter algorithms for bare earth extraction from airborne laser scanning point clouds, ISPRS Journal of Photogrammetry and Remote Sensing, 59(1–2):85–101.

Sohn, G., Cho, W. and Tao, V., (2008): An implicit geometric regularization of 3D building shape using airborne LiDAR Data. IAPRSIS XXXVII-B3A:69-76.

Sohn, G., Dowman, I., (2002): Terrain surface reconstruction by the use of tetrahedron model with the MDL criterion. IAPRS, Vol. 34, Part 3A, pp. 336-344.

Sohn, G., and I. Dowman, (2003): Building extraction using LiDAR DEMs and IKONOS images, International Archives of Photogrammetry and Remote Sensing, WG III/3 Workshop on 3-D Reconstruction from Airborne Laser scanner and InSAR Data, Dresden, Germany, 08–10 October, Vol. 34, 3/W13.

Sohn, G., Dowman, I., (2007): Data fusion of high-resolution satellite imagery and LiDAR data for automatic building extraction. ISPRS Journal of Photogrammetry and Remote Sensing 62(1), 43-6.

Suveg, I., and G. Vosselman., (2004): Reconstruction of 3D building models from aerial images and maps, ISPRS Journal of Photogrammetry and Remote Sensing, 58(3–4):202–224.

Tao, G., Yasuoka, Y., (2002): Combining high resolution satellite imagery and airborne laser scanning data for generating bare land dem in urban areas. In: IAPRS, Vol.34 (Part 5/W3): 6 pages.

Toth, C. (2010): Airborne LiDAR technology: the state-of-the-art and future trends. In Latin American Remote Sensing Week Regional ISPRS Conference. 4-8 October 2010, Santiago, Chile.

Verma V., Kumar R., Hsu S. 3D building detection and modeling from aerial LiDAR data. Proceedings of CVPR '06: The 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition; New York, NY, USA. June 17–22, 2006; pp. 2213–2220.

Vosselman, G., Maas, H., (2001): Adjustment and filtering of raw laser altimetry data. Proc. of OEEPE workshop on airborne laserscanning and interferometric SAR for detailed digital elevation models, 1-3 March, pp.62-72.

Vosselman, G., B.G.H. Gorte, G. Sithole, and T. Rabbani, (2004): Recognising structure in laser scanner point clouds, International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 46, 33-38.

Vosselman, G., (2000): Slope based filtering of laser altimetry data, International Archives of Photogrammetry and Remote Sensing, Vol. 33, Part B3/2, Amsterdam, the Netherlands, pp. 935–942.

Vu, T., Yamazaki, F. and Matsuoka, M., 2009. Multi-scale solution for building extraction from LiDAR image data. International Journal of Applied Earth Observation and Geoinformation, 11(4), pp. 281–289.

Wang,Z., and Schenk,T.,(2000): Building Extraction and Reconstruction from LiDAR Data, Int. Archives Photogrammetry Remote Sens., vol. 33, part B3, Amsterdam, The Netherlands, 2000.

Wagner, W., Ullrich, A., Melzer, T., Briese, C. and Kraus, K., (2004): From single-pulse to full-waveform airborne laser scanners: potential and practical challenges. In: IAPRS, Vol. 35 (Part B3): 201–206.

Wang O. and Suresh K. L., David P. H., (2006): A Bayesian Approach to Building Footprint Extraction from Aerial LiDAR Data, University of California, Santa Cruz.

Weidner, U., Foerstner, W., (1995): Towards automatic building extraction from high-resolution digital elevation models. ISPRS Journal of Photogrammetry and Remote Sensing 50(4), pp.38 - 49.

Zhang, K., Chen, S., Whitman, D., Shyu, M., Yan, J., Zhang, C., (2003): A progressive morphological filter for removing non-ground measurements from airborne LiDAR data. IEEE Transactions on Geoscience and Remote Sensing, 41, pp. 872-882.