

AUTOMATED 3D CITY MODELLING AND THE IMPORTANCE OF QUALITY ASSURANCE TECHNIQUES

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ABSTRACT:

Building reconstruction is essential in applications such as urban planning, telecommunication network planning, flight simulation and vehicle navigation which are of increasing importance in urban areas. This paper introduces a new method for automated building reconstruction by fusing airborne optical data with LiDAR point clouds. The data consists of aerial digital imagery acquired with the Leica ADS40, and LiDAR data from the ALS50, representing Leica's headquarter facilities in Heerbrugg, Switzerland and the surrounding region. The method employs a semi automated technique for generating the building hypothesis by fusing LiDAR data with stereo matched points extracted from the stereo model. The final refinement of the building outline is performed for each linear segment using the filtered stereo matched points with a least squares adjustment. The roof reconstruction is achieved by implementing a least squares-plane fitting algorithm on the LiDAR point cloud and subsequently neighbouring planes are merged using Boolean operations for the generation of solid features. The report proposes a robust method for the estimation of the vertical accuracy that includes the generation of raster Digital Surface Models for each building. With the use of DSMs, functions such as overlaying and subtraction with the reference DSMs can provide a robust estimation of the vertical accuracy using statistical parameters. The assessment is particularly encouraging with the building detection percentage of 96% and the overall quality in the range of 89-90%. Based on the reference building models a vertical accuracy assessment is performed, for a selection of 17 buildings, indicating a mean vertical shift of -14cm and a standard deviation of 45cm.

1. INTRODUCTION

Building reconstruction is of primary importance in many applications, including urban planning, telecommunication network planning and vehicle navigation which are of increasing importance in urban areas. Unfortunately, manual reconstruction from photogrammetric techniques is time consuming, and not a cost effective solution. Automated techniques and tools for data acquisition from remotely sensed imagery are needed and this is the focus of many current research efforts. Currently most approaches are not designed to reconstruct roof details for dormer windows, chimneys and small building recesses, except where very high density LiDAR data are available. Therefore the goal of an automatic algorithm is to provide a generic building reconstruction function that can be efficient in a variety of different situations. It should present reliable results with data collected from different sensors, and for projects with different specifications regarding the geometric accuracy and the desired level of detail.

Due to varying complexity of different urban scenes, automatic or semi-automatic workflows for building reconstruction should be accompanied by robust quality assurance tools. The existence of these tools is critical to the adoption of automated algorithms in the industry to ensure the final products meet client requirements and project specifications. So far most accuracy assessment studies have been focused on assessing 3D City Models using abstract methods by assessing either the planimetric accuracy of the building footprints or selectively analysing roof shapes. This research presents a robust semi-automated approach for a comprehensive planimetric and

vertical accuracy assessment of all the reconstructed roof structures. It should be noted that the design and reliability of automatic quality assurance methods is a function of the Level of Detail (LoD) of the City Models. The methods described in this report were designed for the lower and mid LoD City Models up to LOD2 (Bildstein, 2005). Figure 1 represents an example of the LoD definition for 3D City Models.

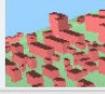
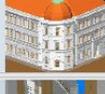
LOD 0		Regional model	2.5D Digital Terrain Model
LOD 1		City/Site model	„block model“ w/o roof structure
LOD 2		City/Site model	textured, with roof structures
LOD 3		City/Site model	detailed architecture model
LOD 4		Interior model	„walkable“ architecture model

Figure 1. LoD definition for City Models, adapted from Bildstein, (2005)

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1.1 Research in Data fusion for 3D City Modelling

Several research efforts confirm that fusion techniques of different datasets for building reconstruction yield superior results. A combination of calibrated aerial images and DSM, produced from LiDAR datasets, was introduced by IGN for several test sites (Kaartinen et al., 2005). The aerial images were used for the semi-automatic production of pseudo-cadastral maps, that described accurately the building outlines, as well as for the automatic production of true-orthophoto.



Figure 2. ADS40 Panchromatic band representing the study area over Heerbrugg-Switzerland

A method proposed by Rottensteiner and Jansa, (2002) combines LiDAR with aerial photographs and performs the polyhedral modeling using Voronoi diagrams. A method proposed from Sohn and Dowman (2006) merges LiDAR with high resolution satellite data, and includes methods for Binary Space Partitioning (BSP), in which a binary tree is incrementally expanded as child polygons are generated by the hyperlines. The final result of the BSP tree is a Building Unit Shape (BUS) adjacent graph where each node represents a BUS and each arc means the connectivity between neighbouring BUSes. A BUS grouping process merges only BUSes, which belong to building structures, and eliminates spurious lines besides building boundaries. As a result, building outlines are reconstructed. A method proposed by Vosselman and Dijkman, (2001) utilizes a 3D Hough transformation for plane extraction combined with existing ground plans. The ground plans can accurately estimate the outline of the roof face and subsequently yield the precise location of the vertical walls.

Building reconstruction using more than two data sources has been introduced also by Chen et al. (2004). This approach combines LiDAR data, aerial imagery and satellite images obtained from the Quickbird sensor. The proposed method is basically a two step procedure that initially detects building regions and then reconstructs the building models. In the stage of building detection, region-based segmentation and knowledge-based classification are integrated.

1.2 Study area and raw data

The study area is situated near Heerbrugg-Switzerland, representing Leica's headquarter facilities as well as the surrounding region (figure 2). The study area, situated approximately 1km west of the centre of Heerbrugg, is representing mostly large industrial buildings with complex roof structures.

These rural regions are very useful for evaluating the influence of the density of the LiDAR point cloud in the building reconstruction process. Various tree canopies of different shape and height are present in the study area, which introduce the necessity for designing a robust and reliable method for vegetation filtering from the LiDAR data.

The data and the supporting material were kindly provided by Leica Geosystems, Heerbrugg for the needs of this project and included, a geo-referenced level 1 stereo-model acquired with Leica's Airborne Digital Sensor (ADS40) and LiDAR data for

the study region obtained with Leica's Airborne Laser Scanner (ALS50).

The ADS40 strip images were acquired from a flight altitude of approximately 2430m, yielding images with photo scale of 1:38900. The entire scene represented in figure 2 is covering an area of 6322 acres with a Ground Sample Distance (GSD) of 0.25m. The LiDAR data consist of two separate point clouds acquired from different flight paths, which intersect at approximately right angles over the study area, having a density of 3-4 points per square metre (figure 3).

2. AUTOMATED CITY MODELLING

2.1 Workflow overview

The individual stages were designed to address the issues introduced in the building reconstruction process with the potential to be fully automated. Although the method utilizes the datasets provided, most of the processing steps were designed in order to be efficient in a variety of different situations. That is, the proposed method is not limited in using for example only sensors that collect multispectral optical data, but instead provide reliable results even when scanned aerial photographs are used. In fact the provided data were limited to panchromatic bands and one green band from the ADS40. Hence, the method had to utilize more generic approaches for solving certain aspects of the processing stages. Nevertheless the crucial aspect of this method is the use of data fusion techniques between two different datasets, optical and LiDAR data in this case, in order to enhance the overall result. The improvement from the proposed method is apparent in both, the generation of the building hypothesis and the building reconstruction phases (Kokkas and Dowman, 2006).

The proposed method consists of four main stages that will be described in the following sections and include the extraction of conjugate points from the optical data, building detection, data fusion for optimizing building outlines and finally the building reconstruction stage.

The process for automatic building reconstruction consists of four major stages that include the automatic feature extraction from the aerial imagery, the building detection from LiDAR or DSMs, the adjustment of the building outlines and small roof details using a geodata fusion process and finally the building reconstruction stage. Figure 3 provides an overview of the proposed method.

2.2 Data Fusion and LiDAR classification

For the process of feature extraction the location of the edges, constituting the vertical walls and additional roof features, are extracted initially from the LiDAR point cloud or DSM and subsequently are refined based on the point features derived from the aerial imagery. The points extracted from stereo pairs of aerial images are automatically matched in the stereo model space and then projected at the object space. The information from the point features will not only refine and improve the accuracy of the building outlines but provide information for smaller roof details that are not modelled correctly in the case of using only coarse LiDAR data or a DSM.

The invention classifies the vegetation using LiDAR data or a DSM by employing a process that scans the surface and match tree shapes according to a library of several tree types as introduced by Kokkas and Dowman, (2006). The main difference of the method compared to previous approaches is the improved robustness by using additional information from aerial images and a library of several tree types. The classification of low features, above the ground, is performed

after the classification of the ground points, where by low features that aren't related with buildings, are filtered using a range of relative heights above the ground surface.

stereo matching algorithm) are inevitable. Therefore there is a high probability having various stereo matched points deviating from the cluster of the LiDAR points representing each

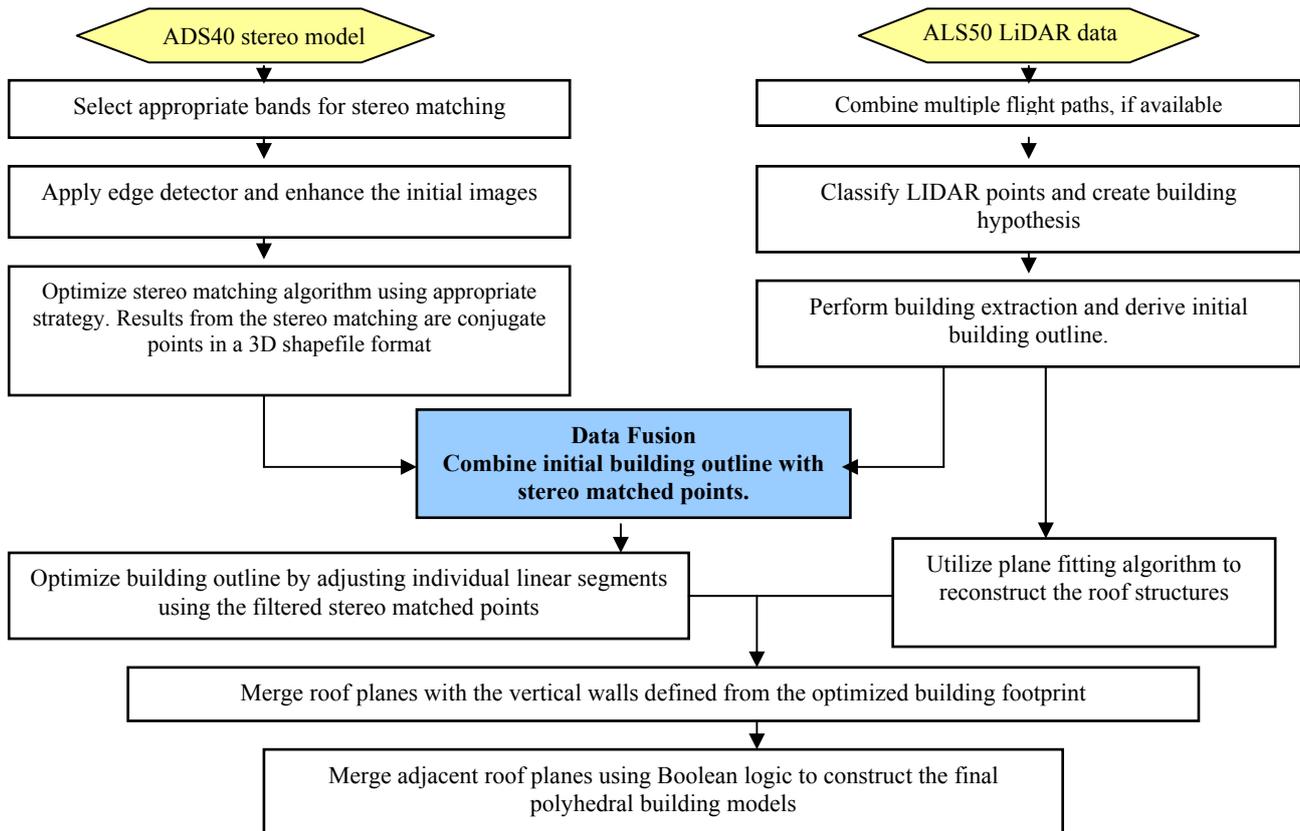


Figure 3. Diagram indicating the overall workflow of the proposed method

The process of building detection and generating the building hypothesis is based on the detection of planar patches on LiDAR point clouds or on a DSM. The initial building hypothesis is subsequently refined by merging the linear features extracted from the aerial images. The adjustment of the building outline is performed for each linear segment using a least squares estimation (Kokkas and Dowman, 2006).

2.3 Polyhedral modelling and final results

The proposed method during the roof reconstruction process utilizes the adjusted building boundaries, accurately representing the outline of the roof face to subsequently yield the precise location of the vertical walls. In addition small roof details are efficiently reconstructed by merging the linear features with the 3D surface patches extracted from the LiDAR point cloud. Subsequently neighbouring planes are merged using Boolean operations for generation of solid features (Kokkas and Dowman, 2006)

From the overall workflow, it can be seen that the creation of a building hypothesis is solely depended on the processing steps applied on the LiDAR points for classifying the data. This stage is briefly outlined in figure 3 but in fact is one of the most complicated stages of the entire project. Another point to note is that the fusion of the two data sources takes place in an advanced stage without having an immediate impact on the reconstruction of the roof planes. Instead data fusion is implemented at the stage of adjusting and refining the building outline which has a direct influence on the vertical walls and the adjacent roof planes. The decision not to merge the stereo matched points with the LiDAR point cloud was based in the valid assumption that a certain degree of mismatches (in the

individual roof plane. This deviation will eventually hinder the roof reconstruction process, because the plane fitting algorithm utilizes a least squares estimation with height tolerances as a termination criterion. Therefore, abrupt height changes between the merged points will potentially disrupt the reconstruction process.

The final stage in the creation of polyhedral building models is the implementation of Boolean functions for merging adjacent roof planes of the same building. The Boolean merging function utilized, is essentially converting the “boundary representation” (individual planar facets) of the buildings into a solid feature. In order for this conversion to be performed the planar facets must be transformed into volume primitives and then merged together using the Constructive Solid Geometry (CSG). Within each building boundary adjacent planes are extended and intersected if they are located within 2m of each other. This buffer region is calculated similarly as the “linear tolerance” during the spatial cleaning, as two times the minimum plane size specified for the plane fitting algorithm (Kokkas and Dowman, 2006).

The proposed method for building reconstruction presents impressive results. The method seems to be very reliable, with most building models visually correct. In addition, the amount of reconstructed roof details is impressive since ventilation equipment, dormers and chimneys were obtained in many cases, see figure 4. The level of detail of the 3D building models is directly related with the density of the point cloud, since no additional features from the aerial photographs are used for the inner roof structures. In contrast the vertical facades of the buildings are created from the refined building footprint with the potential of improving the overall planimetric accuracy of the solid models.



Figure 4. Final reconstructed building models

3. SEMI-AUTOMATED QUALITY ASSURANCE

The reference data for evaluating the planimetric and vertical accuracy of the reconstructed building were obtained from the provided stereo model. The manually stereo plotted buildings represent Leica's facilities and few of the surrounding structures.

The accuracy assessment is divided in the quantitative and qualitative evaluation. The qualitative evaluation includes a visual comparison between the reconstructed buildings (from the combined and single path LiDAR point cloud) and the reference stereo plotted buildings. This comparison will provide a useful indication of the overall quality and therefore, only a selection of the most interesting structures will be illustrated in this section.

The quantitative assessment performed on the reconstructed building models evaluated the planimetric and vertical accuracy. It consisted of a thorough comparison of 17 reference building models situated in Leica's facilities and the surrounding region. The planimetric evaluation is conducted by employing the widely used building detection metrics suggested by Shufelt, (1999). For the vertical accuracy assessment a robust method is proposed for evaluating each building separately, in order to provide statistical parameters for the vertical accuracy.

3.1 Qualitative evaluation of the reconstructed building models

Figure 5 illustrates a selection of the reconstructed buildings that introduced significant differences compared to the reference models. The majority of the buildings in the study area, presented minor differences that weren't able to be distinguished visually.

3.2 Planimetric accuracy evaluation

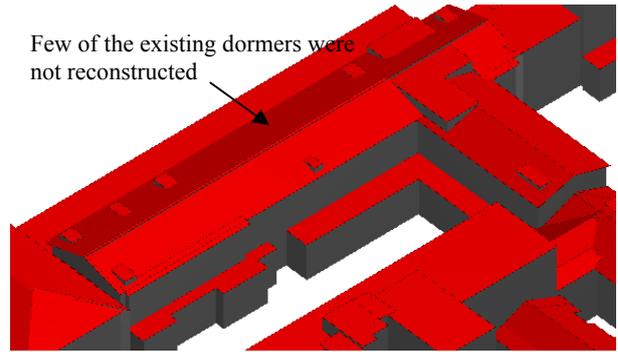
The planimetric accuracy assessment basically attempts to investigate the level of improvement in the horizontal accuracy of the adjusted footprints. The building detection metrics adopted for the evaluation can be defined as:

$$\text{Building Detection Percentage} = 100 \cdot TP / (TP + FN)$$

$$\text{Branching Factor} = FP / TP$$

$$\text{Quality Percentage} = 100TP / (TP + FP + FN)$$

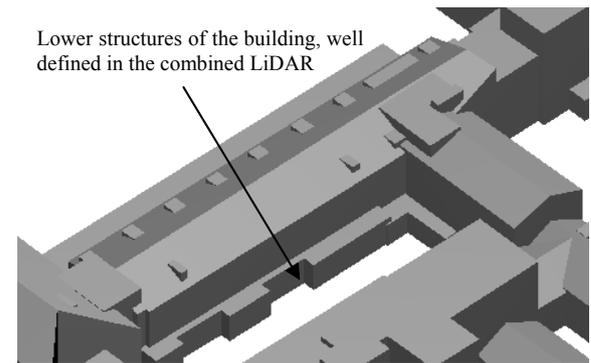
Where TP (True Positive) is a building classified by both datasets, TN (True Negative) is a non-building object classified by both datasets, FP (False Positive) is a building defined only by the automated building reconstruction process, and FN (False Negative) is a building defined only by the reference stereo plotted buildings.



Reconstructed Building from two path LiDAR (4 p/sq.m density)



Reconstructed Building from single path LiDAR (2 p/sq.m density)



Reference Building Models

Figure 5. Quality evaluation of the reconstructed models

The building detection metrics were obtained with basic GIS functions (overlying, clipping), using the building footprints as polygon entities. Consequently the detection metrics are expressed in square meters and not as number of pixels. Using area units of the polygon layers, instead of number of pixels, can increase the precision of the quality statistics. The accuracy assessment (table 1 & 2) presents promising results as the building detection and quality percentage are significantly high.

Building detection metrics for adjusted building outlines derived from the combined LIDAR data			
entire study region	308537 m ²	building detection percentage	97%
true positive	47181.34 m ²		
false positive	4055.17 m ²	Branching Factor	0.0859
false negative	1654.21 m ²		
true negative	255646.28 m ²	Quality Percentage	89%

Table 1. Results from the planimetric accuracy evaluation of the adjusted building outlines, derived from the combined LiDAR

Building detection metrics for initial building outlines derived from the combined LiDAR data			
entire study region	308537 m ²	building detection percentage	96 %
true positive	47035.07 m ²		
false positive	4096.58 m ²	Branching Factor	0.0871
false negative	1805.56 m ²		
true negative	255599.79 m ²	Quality Percentage	88%

Table 2. Results from the planimetric accuracy evaluation of the adjusted building outlines, derived from the combined LiDAR

The Building Delineation Errors (branching factor) are caused when the building outlines are not properly extracted by the automated method. These errors are estimated with respect to the size of the building footprint, defined by both datasets (true positive) and are related to the inherent planimetric accuracy of the input data and subsequently with the point density of the LiDAR point cloud.

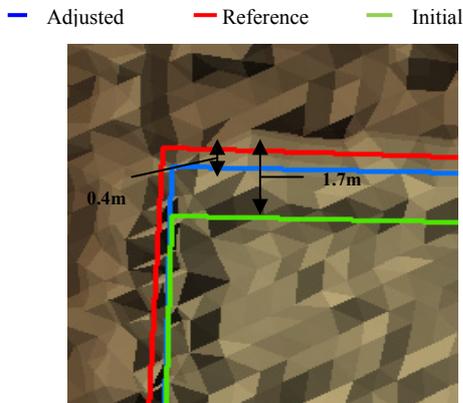


Figure 6 Example of improved planimetric accuracy at the adjusted building footprint.

The accuracy assessment depicted in the previous tables presents promising results as the building detection and quality percentage are significantly high. The building detection percentage was increased in the adjusted building outline as the area of the buildings defined only by the reference stereo plotted buildings (false negative) was decreased. It's worth noting that in both cases the building areas, defined only by the automated procedure (false positive) were similar.

From the estimated detection metrics, it is evident that the differences between the adjusted and the initial footprint are increased. The overall quality has been improved in the adjusted building outlines as it is for the other statistical parameters (figure 6).

At this point it's interesting to note that the planimetric accuracy from the single path LiDAR point cloud is very similar with that obtained from the combined LiDAR data. Although the density of the LiDAR data seems to have a significant negative impact, on the level of reconstructed roof details, the building outlines on the contrary are accurately extracted in both cases.

3.3 Proposed method for automatic vertical accuracy assessment

The proposed method for a robust estimation of the vertical accuracy includes the generation of raster Digital Surface Models for each building. With the use of DSMs, functions

such as overlaying and subtraction with the reference DSMs can provide a robust estimation of the vertical accuracy using statistical parameters. The procedure of creating the DSMs from the 3D building models consists of two basic steps.

- Initially each separate roof plane of the building model is treated undependably to create a TIN plane. Each TIN plane can accurately represent each separate roof plane, since the planes are treated independently.

- The next step includes the conversion of the TIN features into a grid representation. The grid representation has a small spacing to handle even the small boundary details, while the elevation information is stored as a floating point format to preserve the precision of the interpolated elevation values. The TIN to GRID conversion is performed for each roof plane independently.

- Finally the GRID planes (with spacing of 5cm), constituting a single building are merged together using Map Algebra functions. The procedure can be conducted in a GIS environment with scripts, designed to automate the process since for this study area 17 buildings used in the evaluation had over 600 roof planes. Figure 7 depicts a created DSM for a building in the region.

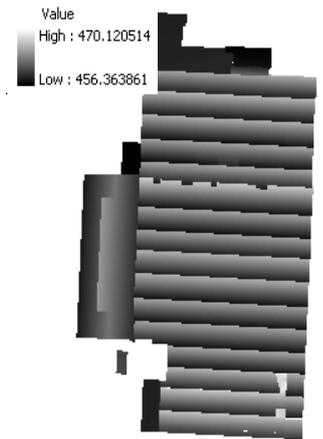


Figure 7. Raster DSM for a building, created from the individual roof planes

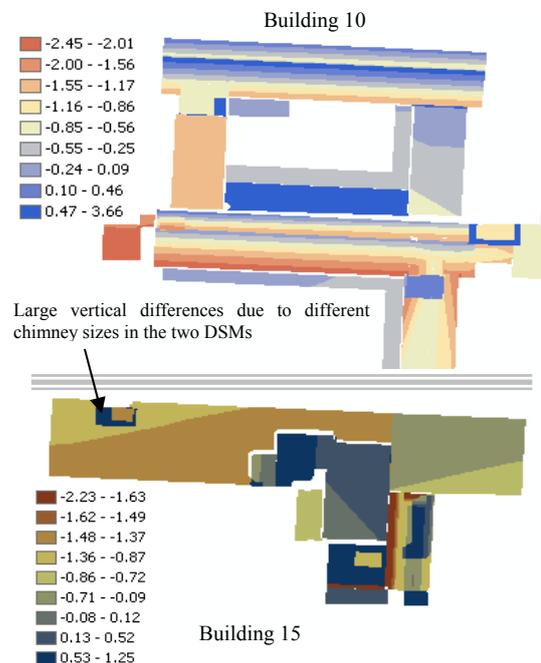


Figure 8. Difference images for buildings 10 & 15, indicating the vertical errors of the two models

The procedure is repeated for the reference 3D building models and the comparison is performed by subtracting the two DSMs. The result is a difference image indicating the height differences between automatically derived and reference roof planes. The difference image is estimated only where the buildings overlap and therefore the calculation of the standard deviation doesn't take into account differences in the footprint

of the buildings (figure 8). The results from the vertical evaluation are summarized in table 3.

Vertical accuracy parameters (3D building models from the combined LIDAR data compared to the reference models)					
Building number	Total pixels	Min. error (m)	Max. error (m)	Mean value(m)	Standard deviation
Building 1	117130	-0.65	1.1	0.34	0.35
Building 2	554643	-0.39	0.97	0.23	0.36
Building 3	810867	-1.27	1.56	0.21	0.53
Building 4	154970	-0.64	2.51	0.61	0.56
Building 5	717449	-1.42	0.36	-0.59	0.48
Building 6	231754	-0.56	0.90	-0.26	0.30
Building 7	133175	-0.99	0.36	-0.49	0.22
Building 8	807336	-0.23	0.09	-0.08	0.07
Building 9	112042	-0.09	0.54	0.16	0.13
Building 10	195849	-2.45	3.63	-0.47	1.09
Building 11	312927	-0.86	0.60	0.12	0.22
Building 12	780007	-2.09	0.62	-0.84	0.39
Building 13	514909	-1.78	0.51	-0.51	0.46
Building 14	460316	-1.10	0.91	0.06	0.31
Building 15	394981	-2.23	1.23	-0.75	0.78
Building 16	605751	-1.20	1.31	0.19	0.58
Building 17	197489	-2.94	1.23	-0.37	0.79
Average values				-0.14m	0.45m

Table 3. Vertical accuracy characteristics of the automatic building models derived from the combined LiDAR data

The results from the evaluation of the automatic building models, derived from the combined LiDAR point cloud, indicate a small overall vertical shift of -14cm. The average standard deviation of the 17 buildings is in the order of 45cm, indicating the presence of vertical errors in the reconstructed roof structures.

4. CONCLUSION AND FURTHER PROSPECTS

This research briefly introduced a method for automated 3D City Modelling previously explained in detail by Kokkas and Dowman. (2006) and introduced a robust approach for automatic accuracy assessment.

The developed method can significantly reduce the time requirements for 3D building reconstruction. Given sufficiently high LiDAR data densities the method is able to provide an increased level of detail and better accuracy than other methods. The results from the accuracy assessment highlight the improvement in the planimetric accuracy of the building footprints and the presence of vertical errors, derived from the proposed method. This is evident also from the maximum and minimum vertical deviation, with building 10 introducing the largest vertical differences in the study area. The majority of the large vertical errors were introduced as a function of the planimetric deviation between the roof planes which is currently one of the main drawbacks of the proposed workflow. An example is the vertical errors introduced when planes representing a dormer in the two DSMs have different sizes. As a result, the planimetric deviations between the DSMs have a significant impact on the estimated standard deviation (figure

8). The presence of vertical errors introduced in the reconstructed roof polygon highlight the need for automatic quality assurance techniques that can indicate the presence of vertical errors for further refinement.

Despite the promising results of the proposed method further research is needed in order to assess the effectiveness of the simplification algorithm, during the adjustment of the building outlines. In addition implementing the proposed method, using different data sources, will be useful in order to evaluate the efficiency of the method in a variety of different situation and scales. The utilization of extracted linear features can also provide additional information that will enhance the roof reconstruction stage and this is the focus of the ongoing research.

5. ACKNOWLEDGMENTS

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