

# QUALITY ASSESSMENT OF 3D BUILDING DATA BY 3D SURFACE MATCHING

Devrim Akca<sup>a</sup>, Mark Freeman<sup>b, \*</sup>, Armin Gruen<sup>a</sup>, Isabel Sargent<sup>b</sup>

<sup>a</sup> Institute of Geodesy and Photogrammetry, ETH Zurich, CH-8093 Zurich, Switzerland  
(akca, agruen)[@geod.baug.ethz.ch](mailto:akca, agruen@geod.baug.ethz.ch), <http://www.photogrammetry.ethz.ch>

<sup>b</sup> Ordnance Survey Research, C530, Ordnance Survey, Romsey Road, Southampton, SO16 4GU, United Kingdom  
(Mark.Freeman, Isabel.Sargent)[@ordnancesurvey.co.uk](mailto:Mark.Freeman, Isabel.Sargent@ordnancesurvey.co.uk), <http://www.ordnancesurvey.co.uk>

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## ABSTRACT:

This is a cooperative work between the Chair of Photogrammetry and Remote Sensing of ETH Zurich and the Research department of Ordnance Survey, called "Quality Assessment of 3D Building Data". The project aims to derive methods to calculate metrics for the quantitative evaluation of 3D building models, which are assumed to be basic elements of a given 3D city model. The developed metrics should respond to customer (of Ordnance Survey) requirements and should be independent of the method of data capture. The input model (3D building data) is co-registered to the verification data using a 3D surface matching method. The 3D surface matching evaluates the Euclidean distances between the verification and input data sets. The Euclidean distances give appropriate metrics for the 3D model quality. The proposed method can favourably address the following quality criteria: reference system accuracy, positional accuracy and completeness.

## 1. INTRODUCTION

In the recent decade the paradigm of man-made object extraction has been shifted to 3D city model generation. 3D city models are in high demand by many public and private organizations.

Airborne imagery and LIDAR are the basic data sources. None of them is solely enough when the automation is concerned. The existing geodata and knowledge (such as 2D ground plans and maps) are mostly used as ancillary data (Haala and Brenner, 1999; Brenner, 2000; Suveg and Vosselman, 2004). Usage of high resolution satellite imagery is also examined (Fraser et al., 2002; Lee et al., 2003). Comprehensive reviews can be found in Mayer (1999), Baltsavias et al. (2001), Baltsavias and Gruen (2003) and Baltsavias (2004).

At the Chair of Photogrammetry and Remote Sensing of ETH Zurich the topic has been initially addressed with a joint project, which aims to develop reliable and geometrically precise image analysis methods towards the Automation of Digital Terrain Model (DTM) Generation and Man-Made Object Extraction from Aerial Images (AMOB). The topics of the research focus on 3D metric and integrative aspects of aerial image processing, in particular on methods for fully automated extraction of DTMs and of man-made objects (Henricsson et al., 1996). The core of the AMOB project consists of a fully automatic system (ARUBA – Automatic Reconstruction of Buildings from Aerial Images) for 3D reconstruction of buildings from aerial images (Henricsson and Baltsavias, 1997).

However, due to the complexity of natural scenes and the lack of performance of image understanding algorithms, the fully automated methods can still not guarantee results that are

stable and reliable enough for practical use (Gruen and Wang, 1998; Foerstner, 1999; Vosselman and Veldhuis, 1999). Early realization of this fact has led to substantial research on the semi-automated methods. The semi-automated methods are a compromise where the image understanding (more specifically object identification and localization) task is undertaken by the operator, while the final topology of the building is established by the algorithm. Sinning-Meister et al. (1996) introduce a semi-automatic approach, including a topology builder algorithm, which automatically fits roof planes to manually measured roof points. Later on, this idea is organized into a more compact form called TOBAGO (Topology Builder for the Automated Generation of Objects from 3D Point Clouds) system (Gruen, 1998). The TOBAGO software essentially solves the automated structuring of 3D point clouds by fitting generic building models (from a roof catalogue) to the roof points using the constraint-based reasoning. This later progressed to CC-Modeler (CyberCity Modeler), which is a generalization of the TOBAGO system. CC-Modeler is a generic topology generator, in which the problem of fitting planar faces to point clouds is treated as a consistent labelling by probabilistic relaxation, and can also be used for other objects, e.g. roads, rivers, parking lots (Gruen and Wang, 1998). The CC-Modeler is indeed a 3D GIS system which is far beyond of conventional CAD systems. A recent EuroSDR comparison shows the superior success of CC-Modeler (Kaarinen et al., 2005).

While the performance of the methods is improving, the quality evaluation of 3D building data has become an important issue. It is mostly calculated through the metrics either using pixels based on 2D projections (Henricsson and Baltsavias, 1997; Ameri, 2000; Suveg and Vosselman, 2002; Boudet et al., 2006), or using voxels, considering buildings as volumetric data (McKeown et al., 2000; Schuster and Weidner, 2003; Meidow

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\* Corresponding author.

and Schuster, 2005). Qualitative and visual evaluation based methods are also preferred (Rottensteiner and Schulze, 2003; Durupt, Taillandier, 2006). Elberink and Vosselman (2007) introduced an end-to-end quality analysis (of 3D reconstructed roads) using error propagation applied to the stochastic properties of input data. Detailed reviews can be found in McKeown et al. (2000) and Sargent et al. (2007).

Over the last few years, Ordnance Survey has initiated several projects to look into how the quality of 3D data, particularly building models, can be assessed. In this paper we are designing quality assessment measures that have meaning to users, so as to ensure that we are capturing data to users' requirements and that users understand the fitness of our 3D data for their purposes. We are also testing assumptions made in 3D modelling research about how best to represent real-world detail from the point of view of user requirements (Sargent et al., 2007).

In 2007, a cooperative project was started between the Chair of Photogrammetry and Remote Sensing of ETH Zurich and the Research department of Ordnance Survey, called 'Quality Assessment of 3D Building Data'. The project aims to derive methods to calculate metrics for the quantitative evaluation of 3D buildings, which are assumed to be the basic elements of a given 3D city model. Metrics and methods should correspond to customers' requirements (of Ordnance Survey) and should be independent of the method of data capture.

The input data to be assessed are 3D building models provided in CC-Modeler (CyberCity AG, Zurich) format. The verification (reference) data is either airborne laser scanning (ALS) point cloud data and/or another 3D model that is given at a presumably higher quality level.

In fact, 3D building data is in surface model form. Thus, pixel or voxel representations are sub-optimal. We propose a method, which directly works on 3D surface elements (surfels). The input model is co-registered to the verification data by use of the Least Squares 3D surface matching method (LS3D, Gruen and Akca, 2005). The LS3D method evaluates the Euclidean distances between the verification and input data sets. The Euclidean distances give appropriate metrics for the 3D model quality.

## 2. QUALITY ASSESSMENT BY SURFACE MATCHING

### 2.1 Least Squares 3D surface matching

We propose a quality evaluation method for 3D building data by use of the least squares 3D surface matching method. It is a rigorous algorithm for the matching of overlapping 3D surfaces.

The LS3D estimates the transformation parameters between two, or more, fully 3D surfaces, using the Generalized Gauss-Markoff model, minimizing the sum of squares of the Euclidean distances between the surfaces. This formulation gives the opportunity of matching arbitrarily oriented 3D surfaces simultaneously, without using explicit tie points. The geometric relationship between the conjugate surfaces is defined as a 7-parameter 3D similarity transformation. This parameter space can be extended or reduced, as the situation demands it. The unknown transformation parameters are treated as stochastic quantities using proper *a priori* weights.

The mathematical model is a generalization of the Least Squares image matching method, in particular the method given by Gruen (1985). It provides mechanisms for internal quality control and the capability of matching of multi-resolution and multi-quality data sets. For details we refer to Gruen and Akca (2005).

This method was originally developed for the co-registration of point clouds and surfaces. Recently, it has also been used for inspection, comparison and validation studies (Akca, 2007).

The proposed method can address the following quality criteria:

- **Reference system accuracy:** Due to differences in production techniques, the reference frames of the input and verification data sets may differ, e.g. positional shifts and angular tilts. The LS3D algorithm calculates any translational, rotational and scaling differences between the two data sets with their associated theoretical precision values.
- **Positional accuracy:** The LS3D surface matcher establishes the 3D correspondences for each (point or surfel) element of the verification data onto the surfels of the input data. In fact, each correspondence is a 3D Euclidean distance vector. Assuming that the verification data are available at a higher quality level and in an appropriate point density, the Euclidean distances show the positional accuracy of the individual surfels of the input surface.
- **Completeness:** The non-measured/missed points/features/buildings are the real problem. Currently, there is no practical way to check fully automatically for this deficiency. Only through comparison with verification data, or through visual checks, can one get quality measures. Assuming that the verification data set is complete, accurate and dense enough, the LS3D surface matcher can provide completeness criteria, including the omission (type I) and commission (type II) errors. For the 3D building case, the omission error describes the rejected or missing buildings (partially or entirely). This means that some elements of the verification data will not have a correspondence to the input data. Commission error is the acceptance of non-building objects as buildings. They appear as some surfels of the input data, but will not receive a correspondence from the verification data.

### 2.2 Quality assessment strategy

Three procedural steps were followed in the experiments. At the first step, the LS3D software was run without any 3D transformation calculation. It was run for one iteration. Only the 3D spatial distances (Euclidean distances) from LIDAR points to the corresponding 3D building triangles were calculated. This step was to show the initial (spatial) agreement of both data sets before applying a 3D similarity transformation (Figure 1). At this stage, the errors are composed of at least two components: errors due to the reference system and the positional errors of individual buildings. These errors are factorized by the subsequent step.

At the second step, a full LS3D surface matching was performed. It calculated any translational, rotational and scale

difference between the verification and test data sets. According to our preliminary tests, there are only translational differences (spatial shifts) between both data sets. The rotational and the scale differences are not significant. Then, the LS3D software was run in 3 degrees of freedom (DOF) mode. This step shows the reference system accuracy of the building models with respect to the coordinate system of the LIDAR data. The estimated 3D transformation parameters (held as a translation vector) were applied to the test data sets. Thus, the reference system errors were isolated from the individual building errors.

At the third step, the last LS3D run was applied, but again without any 3D transformation calculation. Only the correspondences were computed. This final step shows the positional accuracy of individual buildings and the completeness.

The procedure was implemented as a MS Windows application with a graphical user interface (GUI) using the C/C++ programming language.

### 2.3 Correspondence search

Correspondence search is the most computationally expensive part of every surface matching algorithm. There are many ways to reduce the search space, and thus the computational burden. In the basic implementation, we use a 3D boxing based search algorithm. See Akca and Gruen (2005) and Akca (2007) for the details.

Searching the correspondence is guided by the 3D boxing structure, which partitions the search space into cuboids. For a given surface element, the correspondence is searched for only in the box containing this element and in the adjacent boxes. The correspondence is searched in the boxing structure during the first few iterations, and in the meantime its evolution is tracked across the iterations. Afterwards the search process is carried out only in an adaptive local neighbourhood according to the previous position and change of correspondence. In any step of the iteration, if the change of correspondence for a surface element exceeds a limit value, or oscillates, the search procedure for this element is returned to the boxing structure again.

For the 3D building data quality assessment case, we keep the boxing method, but customized for the new task. For any point of the LIDAR data, the coincident box is calculated. All buildings (entirely or partially) situated in the coincident box or in its 28-neighbourhood are listed. The correspondence is searched only on the triangles of those building.

### 2.4 Outlier detection

Detection of false correspondences with respect to the outliers and occlusions is crucial. We use the following strategy in order to localize and eliminate the outliers and the occluded parts. In the course of iterations a simple weighting scheme adapted from Robust Estimation methods is used:

$$(P)_{ii} = \begin{cases} 1 & \text{if } |(v)_i| < K\hat{\sigma}_0 \\ 0 & \text{else} \end{cases} \quad (1)$$

where  $(v)_i$  is the  $i$ -th correspondence and  $\hat{\sigma}_0$  is the standard deviation of the spatial distances of the current iteration. In our

experiments  $K$  is selected as  $>2.5$  or  $>3$ . For many application cases of Robust Estimation procedure, this is an over-strict number which brings the danger of exclusion of the inliers. On the other hand, when increasing the Robust weighting factor, for example to  $>6$ , the computation usually fails due to impairing effect of the non-relevant points, i.e. points belonging to ground or trees, etc.

## 3. EXPERIMENTAL WORK

The results of our work provide measures of how well an entire building model matches reality and thus help to identify where it differs. This allows us to update our 3D model to create high quality data, for instance a verification building model for further quality assessment research.

We have three test sites in the United Kingdom for the verification of the procedure

- Avonmouth (AV)
- Bournemouth test area 1 (BO1)
- Bournemouth test area 2 (BO2).

The experimental result of only two test sites (AV and BO2) are given here due to page limit of the paper.

Each test site has LIDAR point cloud and 3D building polygon files. The LIDAR point clouds were acquired by Airborne 1 Corporation using a Bravo 50K ALTM system carried on a helicopter platform. They are in 25point/m<sup>2</sup> density and delivered in both ENZI and LAS formats. The LIDAR point clouds are used as verification data in all experiments. 3D building data were generated using the CC-Modeler software by photogrammetric processing of DMC imagery. The final polygon files delivered in standard CC-Modeler V3D file format.

### 3.1 Results of test site AV

**Step 1.** The standard deviation of the spatial distances (sigma naught) before the LS3D surface matching is 0.81 m. Blue indicates that model data (3D building data) are above the verification LIDAR data, while yellow-red indicates the opposite case (Figure 1a). Note that in Step 1 and Step 3, for all test sites, a 2.0 m threshold is used for the Robust re-weighting. This means that all the correspondences whose spatial distance is greater than 2.0 m are not considered in the calculation. This is mainly to exclude the non-relevant points, e.g. points on the terrain, trees, bushes, etc. Note that there is no coverage of LIDAR point clouds for a few houses as seen at the bottom right of Figure 1a.

**Step 2.** The estimated translation parameters (associated with their theoretical precision values) between the LIDAR point cloud and building model reference systems are given below:

|                  |        |        |        |
|------------------|--------|--------|--------|
| Translations (m) | +0.029 | +0.064 | -0.849 |
| (X0,Y0,Z0)       | ±0.002 | ±0.002 | ±0.001 |

During the LS3D surface matching, all the correspondences whose spatial distance is greater than the 3 times of the sigma naught (of the current iteration) are excluded from the calculation (according the formula given in section 2.4). As seen from the Z component of the translation vector, the test V3D model is almost 85 cm higher than the reference LIDAR point cloud data (Figure 1a). This is most probably because of

the coordinate reference differences between the two data sets or any image restitution problem when generating the V3D

data set.

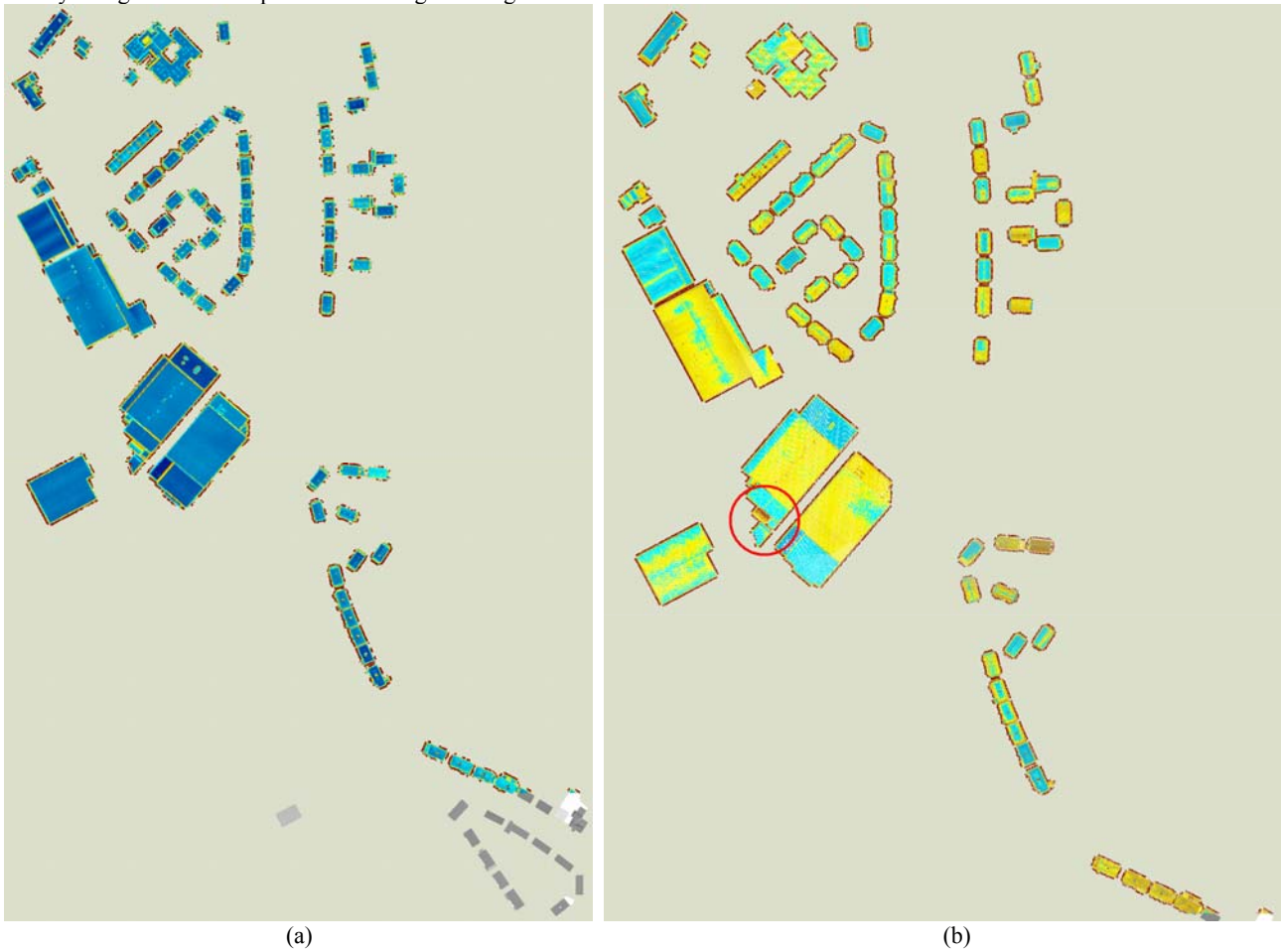


Figure 1. (a) Test site AV before the LS3D surface matching. (b) Test site AV after the LS3D surface matching. The red circle shows a part of a building which has large differences between the model and the point cloud. Ordnance Survey © Crown copyright. All rights reserved.

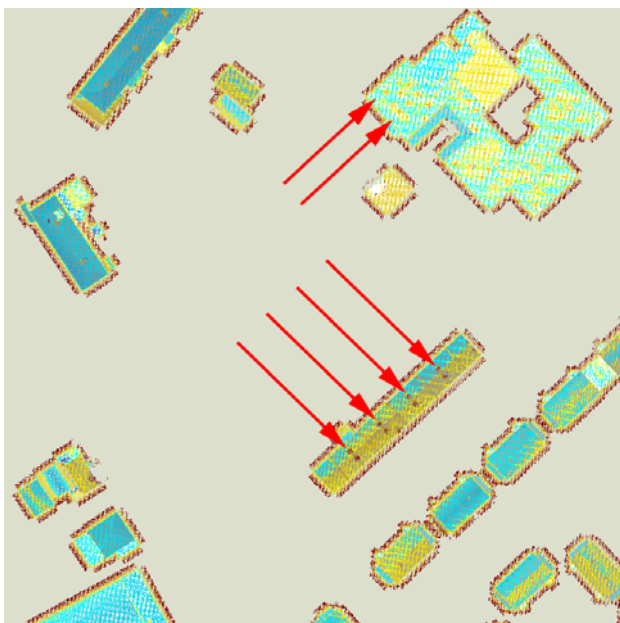


Figure 2. Zoom-in to upper-left part of Figure 1b. The red arrows show the missing chimneys and dormers in the V3D

model data. Ordnance Survey © Crown copyright. All rights reserved.

**Step 3.** The sigma naught is 0.60 m. The Robust threshold value is 2.0 m again. The dark red points at the edges of the buildings (Figure 1b) are due to non-relevant (disturbing) terrain points that the LS3D surface matcher considers to belong to the buildings due to their proximity. The number of the dark-red points is increased from Figure 1a to Figure 1b. In Figure 1a the V3D model is higher than the LIDAR point cloud. When applying the translation by Step 2, the V3D model is shifted to the ground direction, then more ground points come within the Robust threshold value. Thus, 0.60 m of the sigma naught is not solely related to the building inaccuracy. It also includes the effect from those (outlier) ground points. An appropriate strategy is needed to tackle the problem. This issue is discussed in Chapter 3. Red signs in Figure 1b and 2 show some missing parts of the model data as a concern of the completeness.

### 3.2 Results of test site BO2

**Step 1.** Standard deviation of the spatial distances (sigma naught) before the LS3D surface matching is 0.73 m. See Figure 3 for the graphical results.

**Step 2.** The Robust threshold value is set to 2.5 times of the sigma naught (of the current iteration). The translational

reference system difference between the model V3D data and the reference LIDAR data is

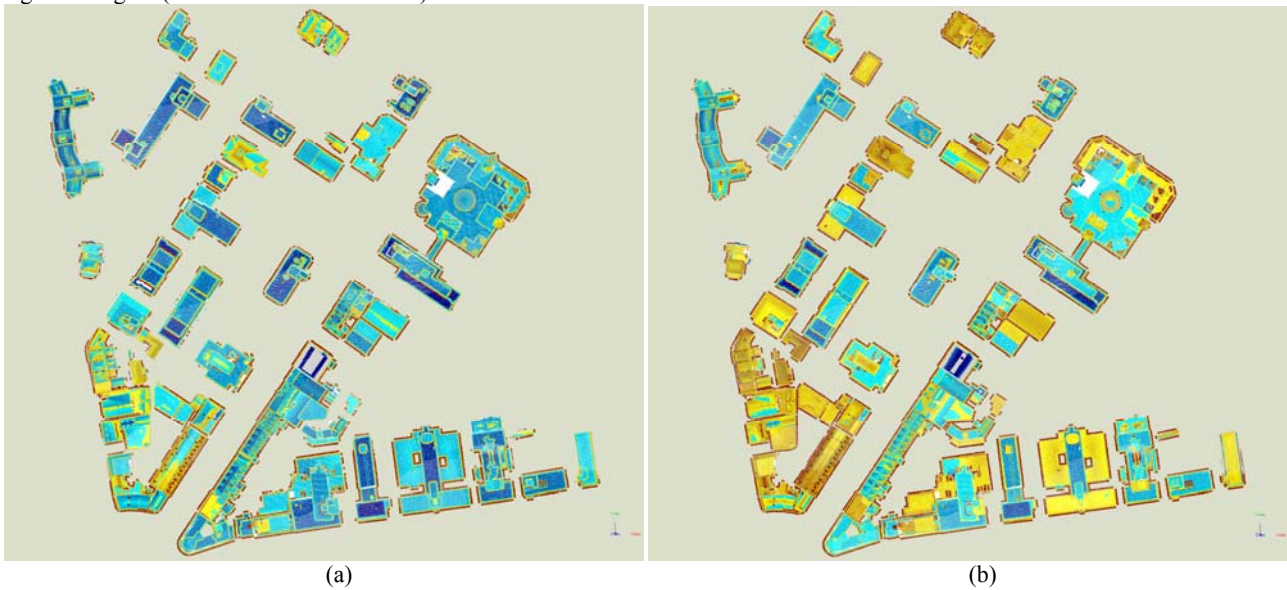


Figure 3. (a) Test site BO2 before the LS3D surface matching. (b) Test site BO2 after the LS3D surface matching after which the errors due to the reference system differences are corrected. Ordnance Survey © Crown copyright. All rights reserved.

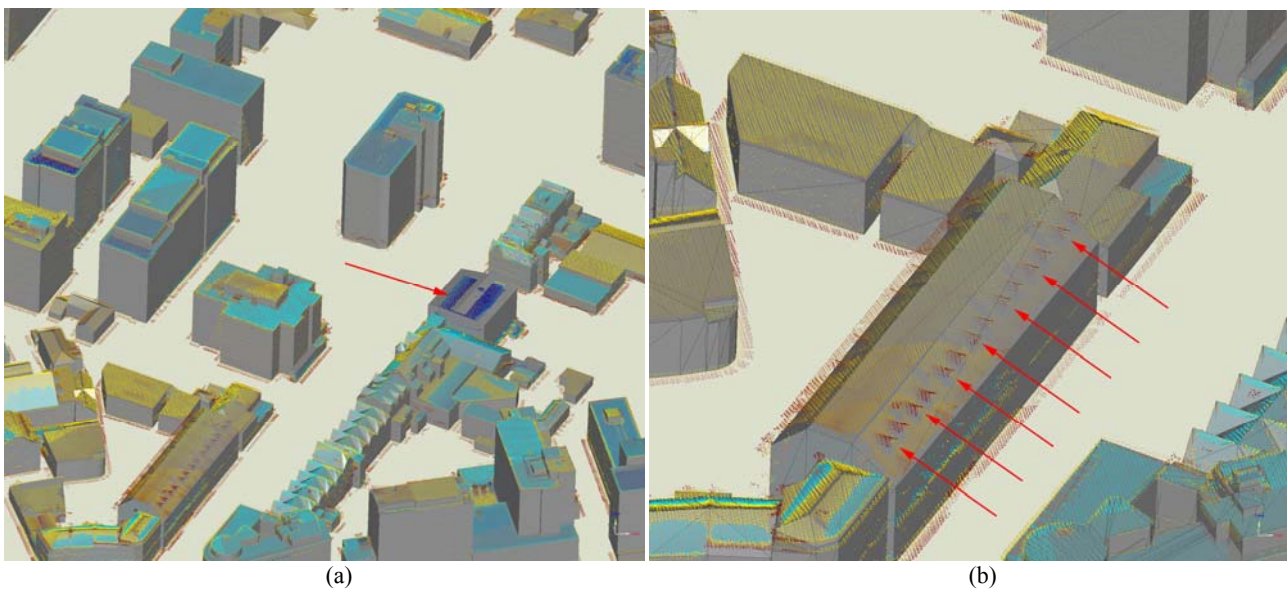


Figure 4. (a) Zoom-in of the central of Figure 3b (oblique view). The red arrow shows a building which was large differences between the model and the point cloud. (b) Zoom-in of the lower-left part of Figure 3b in oblique view. The missing dormers (indicated by the red arrows) can easily be identified by the LS3D surface matcher. Ordnance Survey © Crown copyright. All rights reserved.

|                  |        |        |        |
|------------------|--------|--------|--------|
| Translations (m) | +0.213 | -0.332 | -0.481 |
| (X0,Y0,Z0)       | ±0.001 | ±0.001 | ±0.001 |

**Step 3.** The sigma naught is 0.68 m. The Robust threshold value is 2.0 m again. See Figure 3b, 4a and 4b for the graphical results. From Step 1 to Step 3, the gain is 5 cm in terms of the sigma naught. But, as mentioned before, this is due to disturbing effect of the non-building points. Their magnitude is clearly visible as red buffers at the building borders in Figure 3b. Note that the missing dormers can easily be detected by our approach (Figure 4a and 4b).

#### 4. CONCLUSIONS

2D city maps have rapidly been replaced by 3D city models. While the general emphasis has been to develop tools and methods for automatic city modelling, the concept of quality evaluation has also gained high importance. In this project we have conducted in-depth research into this issue and proposed a practical method, together with GUI-based software. Our method can successfully assess the 3D building data in terms of reference system accuracy, positional accuracy and completeness.

When using the LIDAR point clouds as the verification data, handling of the non-relevant points (points which do not belong to buildings) needs an appropriate strategy. The Robust weighting factor alone cannot solve the problem. Potential solutions which might be considered include:

- (a) filtering the LIDAR point cloud data prior to the processing by a standard algorithm,
- (b) intersection of the LIDAR data and building data along the vertical direction and excluding all non-overlapping LIDAR points,
- (c) in addition to the Robust weighing factor, a second strategy, which determines the LIDAR points belonging to buildings, is embedded to the correspondence search.

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### REFERENCES

- Akca, D., 2007. Least Squares 3D surface matching. Ph.D. thesis, Institute of Geodesy and Photogrammetry, ETH Zurich, Switzerland, Mitteilungen Nr.92, 78 p.
- Ameri, B., 2000. Feature based model verification (FBMV): a new concept for hypothesis validation in building reconstruction. IAPRS 33 (B3), 24-35.
- Baltsavias, E., Gruen, A., and Van Gool, L. (editors), 2001. Automated Extraction of Man-Made Objects from Aerial and Space Images (III), A.A. Balkema Publishers, Lisse, the Netherlands, 415 p.
- Baltsavias, E.P., Gruen, A., 2003. Resolution convergence - A comparison of aerial photos, LIDAR and IKONOS for monitoring cities. Chapter 3. In: Mesev V. (Ed.), *Remotely Sensed Cities*, Taylor & Francis, London, pp. 47-82.
- Baltsavias, E.P., 2004. Object extraction and revision by image analysis using existing geodata and knowledge: current status and steps towards operational systems. ISPRS J. of Remote Sensing & Remote Sensing 58 (3-4), 129-151.
- Boudet, L., Paparoditis, N., Jung, F., Martinoty, G., Pierrot-Deseilligny, 2006. A supervised classification approach towards quality self-diagnosis of 3D building models using digital aerial imagery. IAPRS & SIS 36 (3), 136-141.
- Brenner, C., 2000. Towards fully automatic generation of city models. IAPRS 33 (B3/1), 85-92.
- Durupt, M., and Taillandier, F., 2006. Automatic building reconstruction from a digital elevation model and cadastral data: an operational approach. ISPRS Comm. III Symposium, Bonn, Germany, September 20-22 (on CD-ROM).
- Elberink, S.O., and Vosselman, G., 2007. Quality analysis of 3D road reconstruction. IAPRS & SIS 36 (3/W52), 305-310.
- Foerstner, W., 1999. 3D city models: automatic and semiautomatic acquisition methods. Photogrammetric Week'99, D. Fritsch and R. Spiller (Eds.), Wichmann Verlag, Heidelberg, pp. 291-303.
- Fraser, C., Baltsavias, E., Gruen, A., 2002: Processing of Ikonos imagery for sub-metre 3D positioning and building extraction, ISPRS Journal of Photogrammetry and Remote Sensing, 56, 3, 177-194.
- Gruen, A., 1985. Adaptive least squares correlation: A powerful image matching technique. South African J. of Photogrammetry, Remote Sensing and Cartography, Vol. 14, No. 3, 1985, pp. 175-187.
- Gruen, A., 1998. TOBAGO – a semi-automated approach for the generation of 3D building models. ISPRS J. of Photogrammetry & Remote Sensing 53 (2), 108-118.
- Gruen, A., and Wang, X., 1998. CC-Modeller: a topology generator for 3D city models. ISPRS J. Photogrammetry & Remote Sensing 53 (5), 286-295.
- Gruen, A., Akca, D., 2005. Least squares 3D surface and curve matching. ISPRS J. of Photogrammetry and Remote Sensing, 59 (3), 151-174.
- Haala, N., and Brenner, C., 1999. Virtual city models from Laser altimeter and 2D map data. Photogrammetric Engineering & Remote Sensing 65 (7), 787-795.
- Henricsson, O., Bignone, F., Willuhn, W., Ade, F., Kuebler, O., Baltsavias, E., Mason, S., and Gruen, A., 1996. Project AMOBE: strategies, current status and future work. IAPRS 31 (B3), 321-330.
- Henricsson, O., and Baltsavias, E., 1997. 3D building reconstruction with ARUBA: a qualitative and quantitative evaluation. Int. Workshops "Automatic Extraction of Man-Made Objects from Aerial and Space Images (II)", Ascona, Switzerland, May 5-9, A. Gruen, E. P. Baltsavias and O. Henricsson (Eds.), Birkhäuser Verlag, Basel, pp. 65-76.
- Kaartinen, H., Hyypä, J., Guelch, E., Vosselman, G., et al., 2005. Accuracy of 3D city models: EuroSDR comparison. Int. Workshop "Laser scanning 2005", Enschede, the Netherlands, September 12-14, pp. 227-232.
- Mayer, H., 1999. Automatic object extraction from aerial imagery – a survey focusing on buildings. Computer Vision and Image Understanding 74 (2), 138-149.
- McKeown, D.M., Bulwinkle, T., Cochran, S., Harvey, W., McGlone, C., Shufelt, J.A., 2000. Performance evaluation for automatic feature extraction. IAPRS 33 (B2), 379-394.
- Lee, D.S., Shan, J., and Bethel, J.S., 2003. Class-guided building extraction from Ikonos imagery. Photogrammetric Engineering & Remote Sensing 69 (2), 143-150.
- Meidow, J., and Schuster, H.-F., 2005. Voxel-based quality evaluation of photogrammetric building acquisition. IAPRS & SIS 36 (3/W24), 117-122.
- Rottensteiner, F., and Schulze, M., 2003. Performance evaluation of a system for semi-automatic building extraction using adaptable primitives. IAPRS 34 (3/W8), 47-52.
- Sargent, I., Harding, J., Freeman, M., 2007. Data quality in 3D: gauging quality measures from users' requirements. 5-th Int. Symposium on "Spatial Data Quality", Enschede, the Netherlands, June 13-15 (on CD-ROM).
- Schuster, H.-F., Weidner, U., 2003. A new approach towards quantitative quality evaluation of 3D building models. ISPRS Comm. IV Joint Workshop "Challenges in Geospatial Analysis", Stuttgart, Germany, September 8-9 (on CD-ROM).
- Sinning-Meister, M., Gruen, A., Dan, H., 1996. 3D city models for CAAD-supported analysis and design of urban areas. ISPRS J. Remote Sensing & Remote Sensing 51 (4), 196-208.
- Suveg, I., and Vosselman, G., 2002. Mutual information based evaluation of 3D building models. Pattern Recognition (ICPR), Quebec City, Canada, August 11-15, vol. 3, pp. 557-560.

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

Vosselman, G., and Veldhuis, H., 1999. Mapping by dragging and fitting of wire-frame models. *Photogrammetric Engineering & Remote Sensing* 65 (7), 769-776.

