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# QUALITY ASSESSMENT OF 3D BUILDING DATA

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*Abstract*

*Three-dimensional building models are often now produced from lidar and photogrammetric data. The quality control of these models is a relevant issue both from the scientific and practical points of view. This work presents a method for the quality control of such models. 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. This metric is independent of the method of data capture. The proposed method can favourably address the reference system accuracy, positional accuracy and completeness. Three practical examples of the method are provided for demonstration.*

Keywords: 3D building model, 3D comparison, lidar, point cloud, quality assessment, surface co-registration

## Introduction

For about 20 years, 3D city modelling has been an important research and development issue in geomatics. Many different techniques have been proposed, especially for reality-based concepts. Reviews can be found in Mayer (1999), Grün (2000), Baltsavias et al. (2001), Baltsavias and Gruen (2003) and Baltsavias (2004). Three-dimensional city models have become one of the most significant products of the geospatial industry, required as part of many new applications (Gruen, 2001). Reality-based models are now produced using a variety of different source data and sensors (maps, GIS data, cameras of different types, lidar), operating from various platforms: spaceborne (satellites); airborne (survey aircraft and unpiloted aerial vehicles (UAVs)); and terrestrial (mobile mapping and street images).

While the methods for generating virgin data-sets efficiently and reliably are still being developed and optimised, little has been done with respect to the quality control of such data and the updating and maintenance of the models.

As the performance of the data acquisition methods improves, the quality evaluation of 3D building data has become an important issue, particularly in professional practice. So far, quality has been assessed by calculating metrics using either pixels, based on 2D projections (Henricsson and Baltsavias, 1997; Ameri, 2000; Suveg and Vosselman, 2002; Boudet et al., 2006), or voxels, considering buildings as volumetric data (McKeown et al., 2000; Schuster and Weidner, 2003; Meidow and Schuster, 2005). Methods based on qualitative and visual evaluation have also been used (Rottensteiner and Schulze, 2003; Durupt and Taillandier, 2006). In Rottensteiner (2006), the root mean square (rms) errors of the coordinate differences of corresponding vertices in the reconstructed 3D model and the reference model were evaluated. Recently, 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 past few years, the Ordnance Survey of Great Britain has initiated several projects to look into how the quality of 3D data, particularly building models, can be assessed. Ordnance Survey has also tested assumptions made in 3D modelling research about how best to represent real-world detail from the point of view of user requirements (Capstick et al., 2007; Sargent et al., 2007). In 2007, a cooperative project entitled "Quality Assessment of 3D Building Data" was started by the Chair of Photogrammetry and Remote Sensing of ETH Zurich and Ordnance Survey Research. 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. The metrics and methods should correspond to the requirements of customers (of Ordnance Survey) and should be independent of the method of data capture. The outcomes of the project are presented in this paper, following on from the preliminary presentation at the International LiDAR Mapping Forum (ILMF 09) (Akca et al., 2009).

This work included the design of a quality assessment method that has practical meaning to users, so as to ensure that data is captured according to users' requirements and that users understand the quality of the 3D data for their purposes. Three-dimensional building data-sets are presented in the form of 3D surface models. For that, the existing pixel- or voxel-based representations are only indirect approaches and thus suboptimal. This work proposes a method which directly works on 3D surface elements (surfels). Thus, 3D building data can be evaluated in its original form, avoiding projection or resampling errors. The advantage of this methodology is the treatment of the problem in the actual 3D surface representation domain.

The input model is co-registered to the verification data by use of the least squares 3D surface matching (LS3D) method (Gruen and Akca, 2005; Akca, 2010). The input data-sets to be assessed are 3D building models. The verification (reference) data is either airborne laser scanning (ALS) point cloud data or another 3D model that is given at a presumably higher quality level. The LS3D method evaluates the Euclidean distances between the verification and input data-sets. The Euclidean distances give appropriate metrics for the 3D model's quality.

The following two sections introduce the 3D surface matcher and the quality assessment strategy. When the ALS point clouds are used as the reference, irrelevant points (such as those belonging to terrain or vegetation) should be excluded. Details of a filtering process using the SCOP++ LIDAR software are given in the next section, followed by the results of experiments conducted at three test sites in the UK.

## Quality Assessment by 3D Surface Matching

### *Least Squares 3D Surface Matching*

The quality assessment is done by co-registering the input 3D building model data to the verification data. The verification data is fixed, and the input model data is transformed to the spatial domain of the verification data by use of the least squares 3D surface matching method.

The LS3D method is a rigorous algorithm for the matching of overlapping 3D surfaces and/or point clouds. The mathematical model is a generalisation of the least squares 2D image matching method (Ackermann, 1984; Pertl, 1984; Gruen, 1985). It estimates the transformation parameters of one or more fully 3D surfaces with respect to a template surface (which is the verification data here), using the generalised Gauss–Markov model, minimising the sum of the squares of the Euclidean distances between the surfaces. This formulation gives the opportunity to match arbitrarily oriented 3D surfaces, without using explicit tie points.

The solution is iterative. In each iteration a correspondence operator searches the surface-to-surface correspondences between the verification and input data-sets. For each element of the verification data, a conjugate surface element of the input model is found. These (element-to-element) correspondence vectors constitute the essence of the assessment strategy. They numerically show how well the input model fits the verification data.

The geometric relationship between these conjugate surface correspondences is defined as a 7-parameter 3D similarity transformation. This parameter space can be extended or reduced, as the situation demands it. The theoretical precisions of the estimated transformation parameters and the correlations between them can be checked through the a posteriori covariance matrix, which gives useful information about the statistical quality of the parameters. The LS3D method provides mechanisms for internal quality control and the capability of matching multi-resolution and multi-quality data-sets.

More details are given in Gruen and Akca (2005). The method was originally developed for the co-registration of point clouds and surfaces. Recently, it has also been used for 3D comparison, change detection, quality inspection and validation studies (Akca, 2007; 2010).

### *Correspondence Search*

For every surface element of the verification data, the correspondence operator seeks a location at a minimum Euclidean distance away on the input model surface. The verification data surface elements are represented by the data points. Accordingly, the procedure becomes a point-to-plane distance computation assuming that the input building model is represented in a triangulated irregular network (TIN) form. When a minimum Euclidean distance is found, a subsequent step tests the matching point to determine whether it is located inside the input model surface element (point-in-triangle test). If not, this element is disregarded and the operator moves to the next surface element with the minimum distance. Hypothetically, the correspondence criterion searches a minimum magnitude vector that is perpendicular to the input model surface triangle and passes through the verification data point.

Correspondence search is the most computationally expensive part of the algorithm. There are many alternatives to reduce the search space, and thus the computational burden. In the basic implementation, a 3D boxing-based search algorithm is used. 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 for in the boxing structure during the first few iterations and meanwhile 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. If in any step of the iteration 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. See Akca and Gruen (2005) and Akca (2007; 2010) for the details.

For the assessment of 3D building data quality, the boxing structure is established for the input 3D building models. For any point of the verification data, the coincident box is calculated. All buildings (entirely or partially) situated in the coincident box or in its "27-neighbourhood" are listed. The correspondence is searched only on the triangles of these buildings.

### *Outlier Detection*

Detection of false correspondences caused by outliers and occlusions is crucial. The following strategy is employed in order to localise and eliminate outliers and occluded parts. During the iterations, a simple weighting scheme, adapted from robust estimation methods, is used:

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

where vector $(\mathbf{v})_i$ is the Euclidean distance of the $i$th correspondence and $\hat{\sigma}_0$ is the standard deviation of the Euclidean distances of the current iteration. In the experiments $K$ is selected as $\geq 4$. For many application cases of the robust estimation procedure, this is a fairly small number, which carries the danger of exclusion of some correct inliers. On the other hand, when increasing the robust weighting factor, for example, to $\geq 8$ or 10, the computation is usually distorted by the impairing effect of the non-relevant points, such as points belonging to ground or trees.

## Quality Assessment Strategy

Without restricting the generality of the approach it is assumed that the verification data is given as lidar point clouds and the input building model data is represented as a TIN. For quality assessment, three procedural steps are used as follows:

Step 1. Firstly, one iteration of the LS3D algorithm is run, without any 3D transformation calculation. The 3D spatial distances (Euclidean distances) from lidar points to the corresponding 3D building triangles are calculated. This step is to show the initial (spatial) disagreement of the data-sets before applying a 3D similarity transformation. At this stage, the errors are composed of at least two components:

(a) errors due to the reference system differences, and
(b) the positional errors of individual buildings.

These errors are factorised in the subsequent second step.

Step 2. In the second step, a full LS3D surface matching is performed. It calculates any translational, rotational and scale difference between the verification and input data-sets. According to the preliminary tests (conducted with the experimental data presented here), there are only translational differences (spatial shifts) between the data-sets. The rotational and scale differences are not significant. Then, the LS3D algorithm is run in the 3 degrees of freedom 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) are applied to the input data-sets. Thus, the reference system errors are isolated from the individual building errors.

Step 3. In the third step, the final LS3D run is carried out, but again without any 3D transformation calculation. Only the 3D correspondences are computed. The 3D correspondences are vectors showing the 3D spatial deviations between the points of the verification data and the surfels (triangles) of the input data. They are the actual quality indices, and they examine the input model at every verification data point location. This final step shows the positional accuracy of individual buildings and the completeness.

The proposed method can address the following three quality criteria.

### *Reference System Accuracy*

Due to differences in production techniques, the reference frames of the input and verification data-sets may differ, leading, for example, to positional shifts and angular tilts. The LS3D algorithm calculates any translational, rotational and scale differences between the two data-sets, with their associated theoretical precision values.

### *Positional Accuracy*

The LS3D surface matcher establishes the 3D correspondences for every point element, or surfel, of the verification data with respect to the surfels of the input data. In fact, every correspondence is a 3D Euclidean distance vector. Assuming that the verification data is 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 model.

### *Completeness*

The non-measured or missed points/features/building parts are the real problem. Currently, there is no practical way to check fully automatically for this deficiency. Only through comparison with the verification data or through visual checks can quality measures be obtained. Assuming that the verification data-set is complete, accurate and dense enough, the LS3D surface matcher can provide the completeness criteria, which are equivalent to the omission type of gross errors.

For 3D building reconstruction, there are two types of gross error (or outlier), namely, omission (type I or false positive or probability of rejecting a correct null hypothesis) and commission (type II or false negative or probability of accepting a false alternative hypothesis) errors.

The omission error, which represents the criterion for completeness, describes the rejected or missing buildings (partially or entirely). In the methodology presented here, this means that some elements of the verification data will not have any correspondence with the input data. Unfortunately, completeness of the entirely missing buildings cannot be detected, since the lidar point cloud (as verification data) is unstructured. This methodology can only assess the completeness of sub-building parts such as walls, chimneys and dormers.

In the current implementation, the completeness criterion is assessed semi-automatically. The method highlights the final Euclidean distances on the 3D building model graphically (see Figs. 3(b) and 9(b)), thereby assisting the operator to identify the missing 3D model parts.

The commission error is the acceptance of non-building objects as buildings. Assessment of the commission errors is not within the scope of this paper. It will be investigated in a future study.

## Filtering of Ground and Vegetation Points in the Verification Data

When using the lidar point clouds as verification data, handling of the non-relevant points (points which do not belong to buildings) needs an appropriate strategy. The robust weighting factor (equation (1)) alone cannot solve the problem.

In the experiments the SCOP++ LIDAR version 5·4 (Inpho GmbH, Stuttgart, Germany) software package was used for the filtering. SCOP++ LIDAR classifies the lidar point clouds into seven classes: ground, below (outlier points below the ground), building, high vegetation, medium vegetation, low vegetation and unclassifiable. Among them the ground, below and low vegetation classes were discarded; the rest of the point clouds (building, high vegetation, medium vegetation and unclassifiable) were merged into one file and this merged file was used as the verification data.

In complex scenes, SCOP++ LIDAR classifies some parts of buildings (usually parts close to roofs) into the high vegetation or medium vegetation classes. Hence, resulting high vegetation and medium vegetation classes were included in the verification point cloud to ensure the completeness of the buildings.

## Experimental Work

Three test sites in the UK have been used for validation of the procedure:

(a) Avonmouth test area (AV),
(b) Bournemouth test area 1 (BO1), and
(c) Bournemouth test area 2 (BO2).

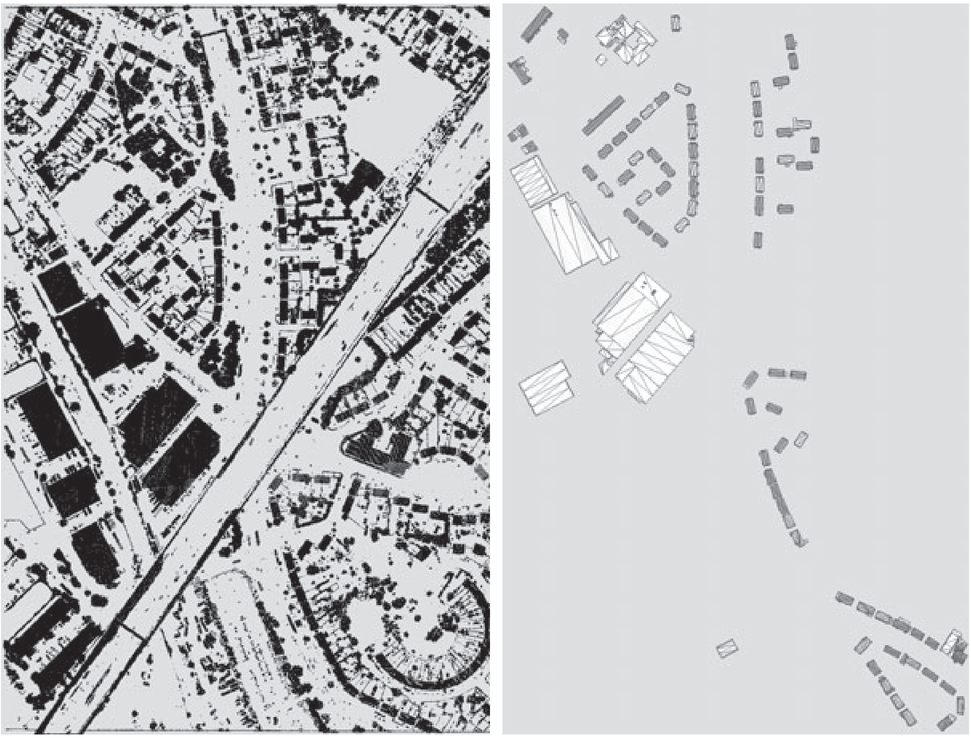
Each test site has a lidar point cloud and a 3D building polygon file. The lidar point clouds were acquired by Airborne 1 Corporation using a Bravo 50K ALTM system carried on a helicopter platform. They had a 25 points/m$^2$ density and were delivered in both ENZI and LAS formats. The lidar point clouds were used as verification data in all experiments.

The 3D buildings were captured using stereopairs of DMC (Intergraph) images from a nadir block with 60% overlap and sidelap. The low-resolution RGB imagery was pan-sharpened with the high-resolution panchromatic image, resulting in imagery with a ground sampling distance (GSD) of approximately 15 cm (flying height around 1500 to 1600 m, focal length 120 cm and pixel size 12 μm). The building measurements were gathered using CC-Modeler software (CyberCity 3D, Inc., El Segundo, CA, USA) in semi-automatic mode by a photogrammetric operator. The final polygon files were delivered in standard CC-Modeler V3D file format.

All experiments were carried out using the LS3D software package, which was developed in-house using the C/C++ programming language and implemented as an MS Windows application with a graphical user interface (GUI).

### *Results of Test Site AV*

The filtered airborne lidar data and associated 3D building data are shown in Fig. 1(a) and (b). The lidar verification data contains 1 706 256 points and the input building model contains



(a) (b)

FIG. 1. Avonmouth test site: (a) filtered lidar point cloud; (b) 3D building model data.


4721 triangles. Note, there is no coverage of lidar data for the few houses seen in the bottom right of Fig. 1(a).

Step 1. The standard deviation of the Euclidean distances (a posteriori $\sigma_0$) before the LS3D surface matching is 0·77 m (Table I). The blue colour indicates that the 3D building data is above the verification lidar data, while yellow-red indicates the opposite case (Fig. 2(a) and (c)). Note that in Step 1 and Step 3, for all test sites, a 2·00 m threshold is used for the robust weighting factor. This means that all the correspondences whose Euclidean distances are greater than 2·00 m are not considered in the calculation. This is mainly done to exclude the non-relevant points such as points on the terrain, trees and bushes.

Step 2. The robust weighting factor is set to 4 times the $\sigma_0$ (of the current iteration). The translation parameters between the reference systems of the lidar point cloud and the building models were estimated as +0·06, +0·05 and −0·85 m for the *X*, *Y* and *Z* axes, respectively. Although the horizontal shift parameters between the lidar reference system and 3D building reference system are not significant, 3D building data is 85 cm above the verification lidar data along the vertical direction. The effect is also seen as change of coloured residuals from Fig. 2(a) and (b). This reference system error is eliminated by applying the estimated translation vector to the 3D building data (Table I).

Step 3. After correcting the reference system errors, $\sigma_0$ was reduced to 0·30 m. The robust threshold value is again 2·00 m. The dark red points at the edges of the buildings (Fig. 3(a) and

TABLE I. Processing results of test site AV.

| *Step* | *Number of correspondences* | *Number of iterations* | *Time (min)* | $\hat{\sigma}_0$ *(m)* | $T_x$ *(m)* | $T_y$ *(m)* | $T_z$ *(m)* | *Stdd-*$T_x$ *(m)* | *Stdd-*$T_y$ *(m)* | *Stdd-*$T_z$ *(m)* |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 457 999 | 1 | 2·6 | 0·77 | n/a | n/a | n/a | n/a | n/a | n/a |
| 2 | 448 664 | 3 | 7·3 | 0·29 | 0·06 | 0·05 | −0·85 | 0·001 | 0·002 | 0·001 |
| 3 | 449 248 | 1 | 2·6 | 0·30 | n/a | n/a | n/a | n/a | n/a | n/a |

$\hat{\sigma}_0$: standard deviation of the Euclidean distances a posteriori.
$T_x$, $T_y$, $T_z$: *X*, *Y*, *Z* components of the estimated translation vector.
*Stdd-*$T_x$, *Stdd-*$T_y$, *Stdd-*$T_z$: theoretical precision of $T_x$, $T_y$, $T_z$.

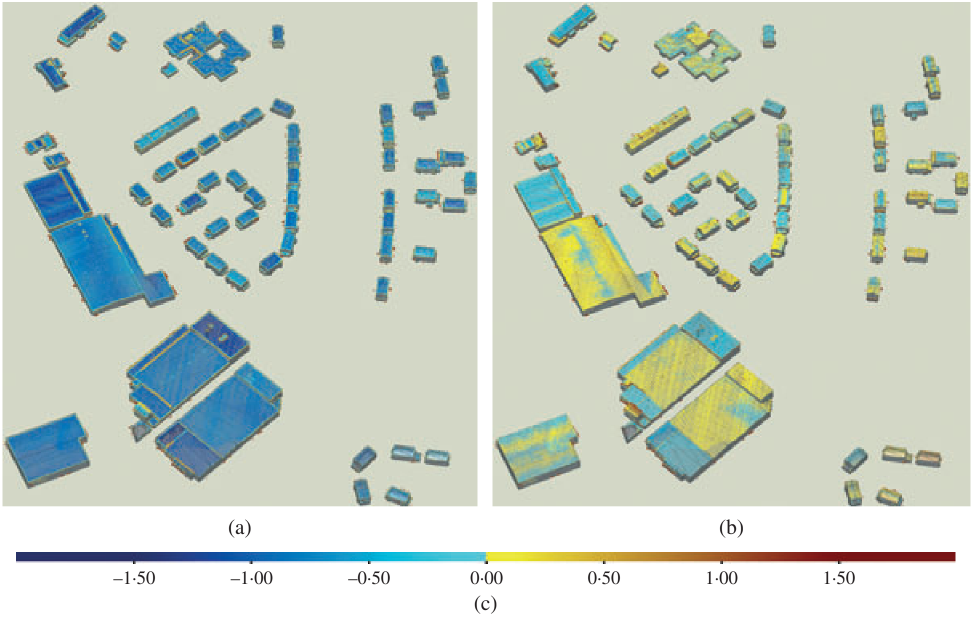
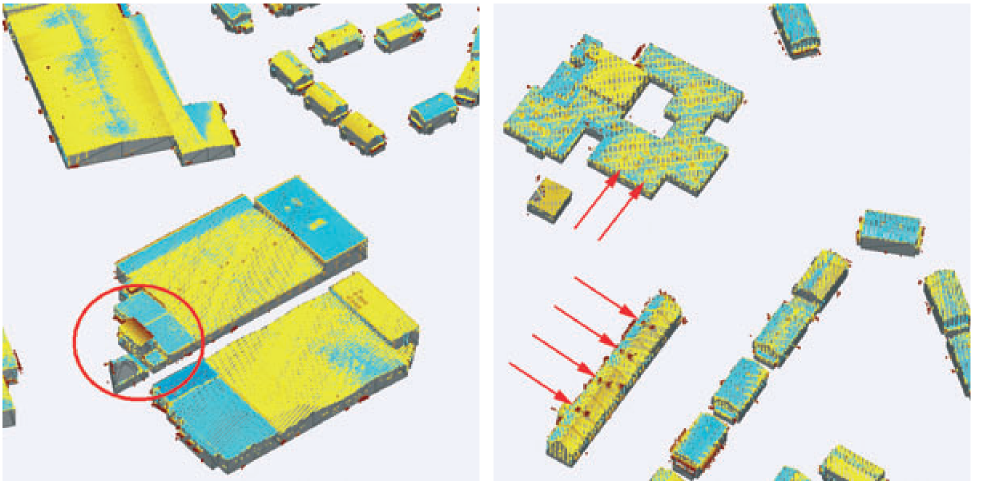



FIG. 2. Avonmouth test site: (a) comparison of verification and input data before LS3D surface matching; (b) after LS3D surface matching; (c) residual bar in metre units. Ordnance Survey © Crown copyright. All rights reserved.

(b)) are due to non-relevant (disturbing) terrain points which the LS3D surface matcher considers to be part of the buildings because of their proximity. Thus, the $\sigma_0$ of 0·30 m is not solely related to building inaccuracy, it also includes the effect from those (outlier) ground points.

In Fig. 3(a) a small roof structure of a building (shown in the red circle) has a large deviation from the verification data, at 1·15 m. This is most probably an operator mistake during the 3D feature compilation process. In Fig. 3(b) the red arrows show some missing chimneys and dormers of the building data, which indicate a lack of completeness. These are again likely to have been omitted by the photogrammetric operator.

As seen in Table I, changing the robust weighting factor affects the number of correspondences found and consequently the a posteriori $\sigma_0$. In Step 2, the robust weighting factor is 1·16 m (4 times the $\sigma_0$ of the current iteration, equivalent to $4 \times 0{\cdot}29$ m = 1·16 m in the last iteration). In Step 3, this was increased to 2·00 m, resulting in more correspondences than Step 2, and accordingly, a slight increase (1 cm) in the a posteriori $\sigma_0$.



(a) (b)

FIG. 3. (a) A zoom-in to the lower-left part of Fig. 2(b). The red circle shows a part of a building which has large differences between the input model and the verification data. (b) A zoom-in to the upper part of Fig. 2(b). The red arrows show the missing chimneys and dormers in the 3D building model data.


### *Results of Test Site BO1*

The filtered airborne lidar data and the input 3D building data are shown in Fig. 4(a) and (b). The lidar data contains 3 229 453 points and the input building model contains 8153 triangles. The scene contains, apart from the others, a large building with complex roof structures (Fig. 4(b)).

Step 1. Standard deviation of the Euclidean distances before the LS3D surface matching is 0·49 m (Fig. 5(a) and Table II). The computation took 11·2 min for 1 445 568 correspondences.

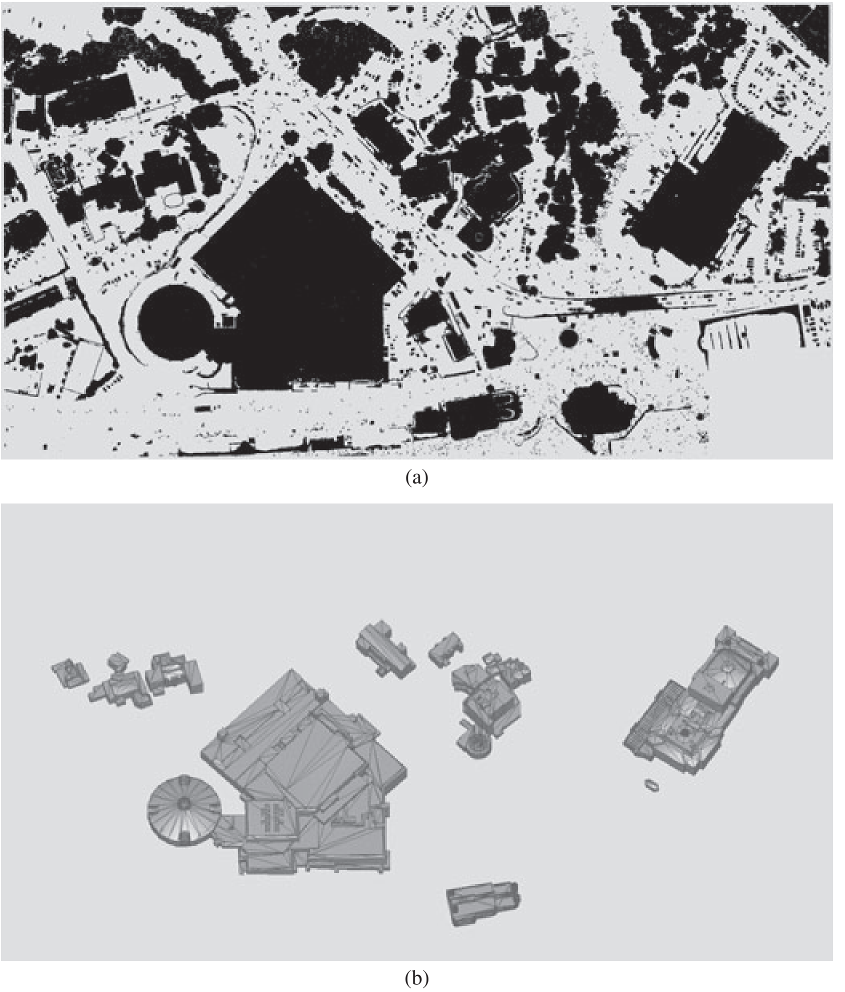
Step 2. The robust threshold value is set to 4 times the $\sigma_0$ (of the current iteration). The translational reference system difference between the model building data and the verification lidar data is +0·11, −0·23 and +0·03 m for the *X*, *Y* and *Z* axes, respectively (Table II). In contrast to test site AV, here the two reference systems differ along the horizontal direction only, and not significantly along the vertical direction.

Step 3. The a posteriori $\sigma_0$ at this step is 0·48 m. The robust threshold value is again 2·00 m. Since the estimated translation parameters (especially the *Z* component) are small, the visual effect of the spatial transformation is not significant (Fig. 5(a) and (b)). Subsequently, the gain from Step 1 to Step 3 in terms of the standard deviations of the Euclidean distances is negligible, at 1 cm. This test site exhibits two interesting measurement error examples.

TABLE II. Processing results of test site BO1.

| *Step* | *Number of correspondences* | *Number of iterations* | *Time (min)* | $\hat{\sigma}_0$ *(m)* | $T_x$ *(m)* | $T_y$ *(m)* | $T_z$ *(m)* | *Stdd-*$T_x$ *(m)* | *Stdd-*$T_y$ *(m)* | *Stdd-*$T_z$ *(m)* |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 445 568 | 1 | 11·2 | 0·49 | n/a | n/a | n/a | n/a | n/a | n/a |
| 2 | 1 443 165 | 7 | 76·0 | 0·47 | 0·11 | −0·23 | 0·03 | 0·001 | 0·001 | 0·001 |
| 3 | 1 447 763 | 1 | 11·7 | 0·48 | n/a | n/a | n/a | n/a | n/a | n/a |

See footnote to Table I for abbreviations.



(a)

(b)

FIG. 4. Test site BO1: (a) filtered lidar point cloud data; (b) 3D building model data.


The dome in Fig. 6(a) was reconstructed using planar triangles and straight lines, although the original shape is curved. This fact is exposed by large deviations in the 3D comparison, gradually increasing up to 1·20 m modelling error. In Fig. 6(b) the roof part of a building model shows large differences with respect to the verification data. This is a measurement error which is larger than 1·5 m.

### *Results of Test Site BO2*

In test site BO2, the filtered reference data is complex and mixed with many points belonging to vegetation (Fig. 7(a)). The lidar point cloud contains 6 797 293 points and the input building model contains 6279 triangles.

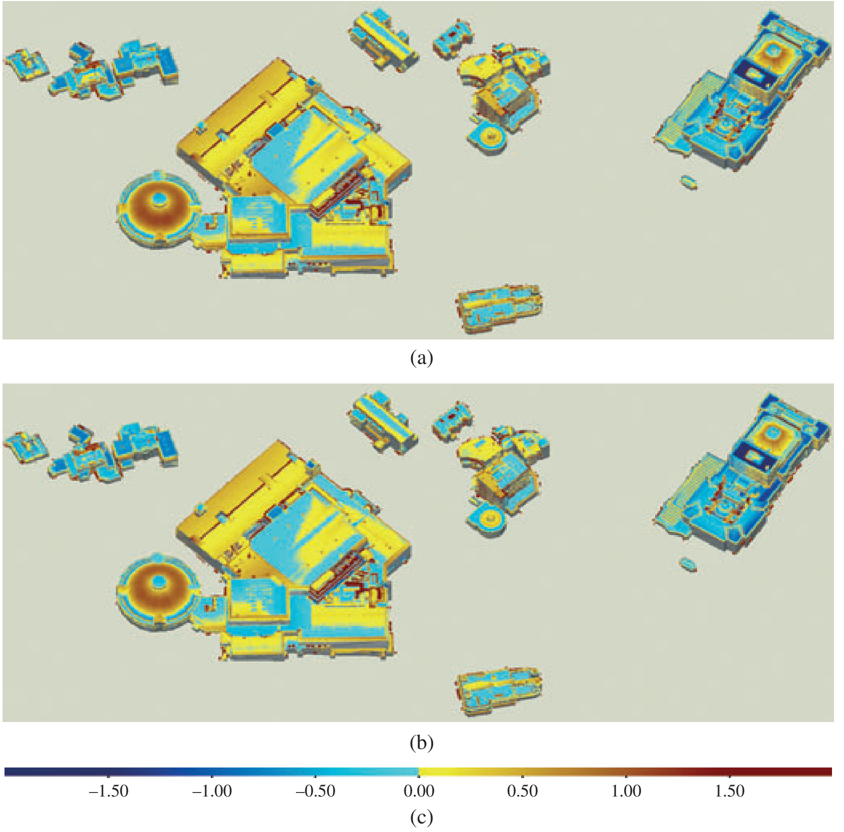
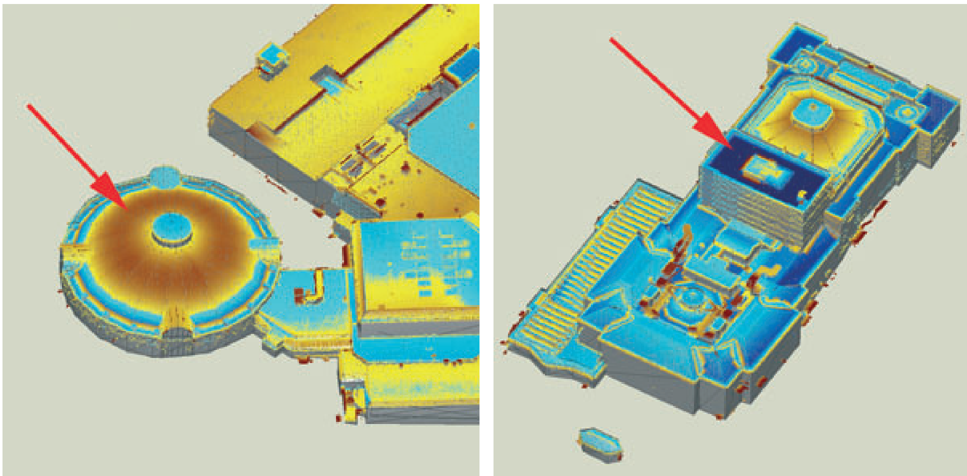



FIG. 5. Test site BO1: (a) comparison of the verification and the input data before the LS3D surface matching; (b) after the LS3D surface matching; (c) residual bar in metre units.


Step 1. The standard deviation of the Euclidean distances before the LS3D surface matching is 0·65 m (Table III). The algorithm computed 999 938 Euclidean distances in 5·3 min. Here, the standard deviation value 0·65 m contains both the reference system errors and building measurement errors. See Fig. 8(a) for the graphical representation.

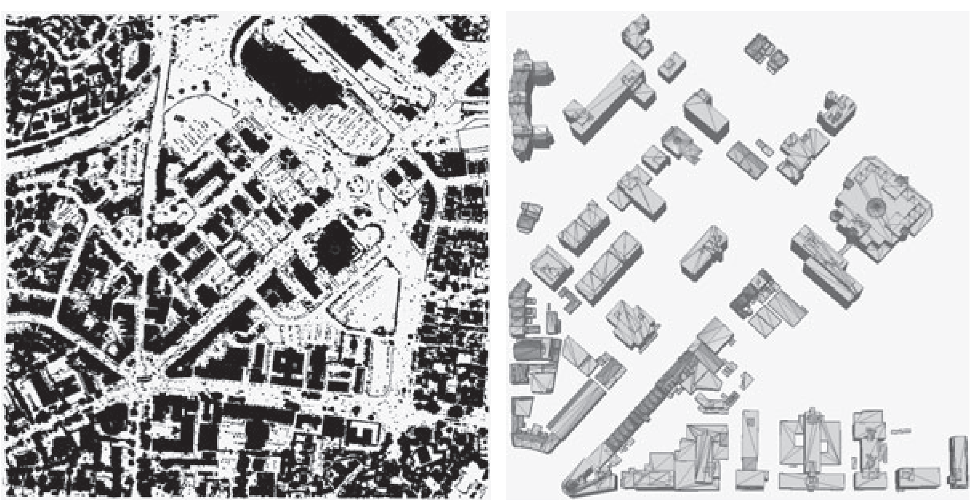
Step 2. The robust threshold value is set to 4 times the $\sigma_0$ (of the current iteration). The translational reference system difference between the building model data and the verification lidar data is +0·24, −0·24 and −0·49 m for the $X$, $Y$ and $Z$ axes, respectively (Table III). Both horizontal and vertical components of the translation vector show numerically significant differences between the two reference systems.

The change of the coloured residuals from Fig. 8(a) to (b) demonstrates the discrepancy graphically. Fig. 8(b) shows the scene after correcting the reference system error (by applying the estimated translation vector to the building model data). The scene now contains only the building measurement errors. The magnitude of the errors of individual building elements has changed considerably. This example shows the importance of the factorisation of the reference system and measurement errors from each other.



(a) (b)

Fig. 6. (a) A zoom-in to the lower-left part of Fig. 5(b). (b) A zoom-in to the upper part of Fig. 5(b). The red arrows in (a) and (b) show a dome and a roof with large deviations from the verification point cloud data. Ordnance Survey © Crown copyright. All rights reserved.



(a) (b)

Fig. 7. Test site BO2: (a) filtered lidar data; (b) 3D building data. Ordnance Survey © Crown copyright. All rights reserved.

Step 3. At this step $\sigma_0$ is 0·54 m. The robust threshold value is 2·00 m again. See Figs. 8(b) and 9(a) and (b) for the graphical results. From Step 1 to Step 3, the gain is 11 cm in terms of $\sigma_0$ (Table III). But, this error budget also contains the disturbing effect of the non-building points. Their magnitude is clearly visible as red buffers at the building borders in Figs. 8(b) and 9(a).

Table III. Processing results of test site BO2.

| *Step* | *Number of correspondences* | *Number of iterations* | *Time (min)* | $\hat{\sigma}_0$ *(m)* | $T_x$ *(m)* | $T_y$ *(m)* | $T_z$ *(m)* | *Stdd-*$T_x$ *(m)* | *Stdd-*$T_y$ *(m)* | *Stdd-*$T_z$ *(m)* |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 999 938 | 1 | 5·3 | 0·65 | n/a | n/a | n/a | n/a | n/a | n/a |
| 2 | 989 870 | 6 | 28·7 | 0·59 | 0·24 | −0·24 | −0·49 | 0·002 | 0·002 | 0·001 |
| 3 | 977 718 | 1 | 5·1 | 0·54 | n/a | n/a | n/a | n/a | n/a | n/a |

See footnote to Table I for abbreviations.

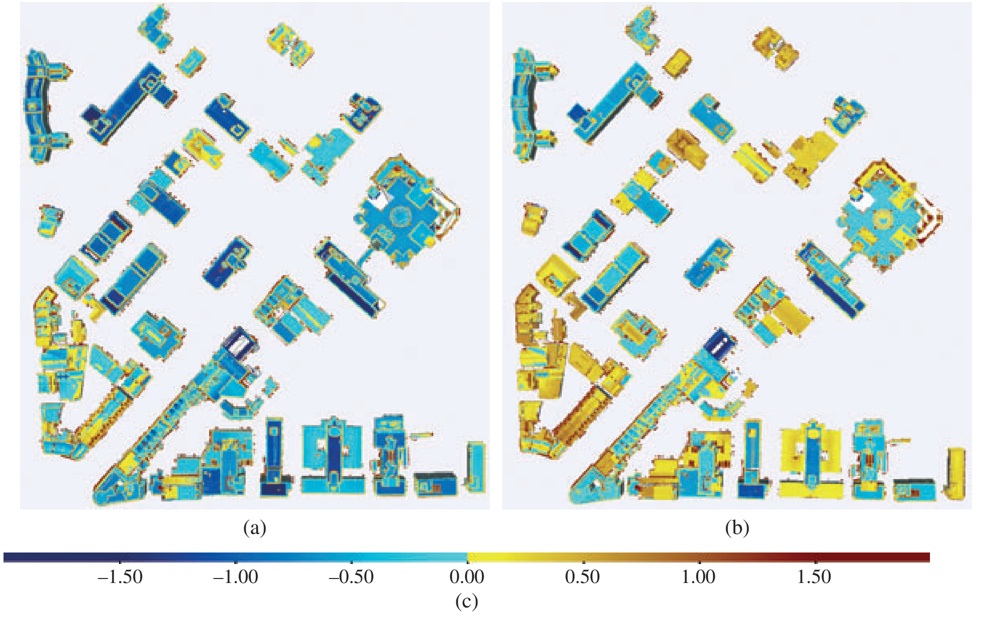
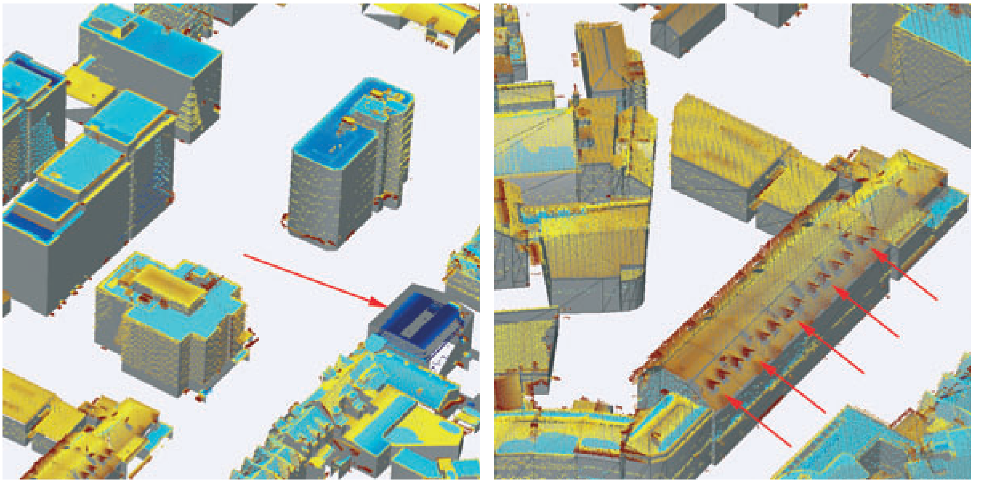



Fig. 8. (a) Test site BO2 before LS3D surface matching. (b) Test site BO2 after LS3D surface matching (the errors due to the reference system differences are now corrected). (c) Residual bar in metre units. Ordnance Survey © Crown copyright. All rights reserved.

In Fig. 9(a) the arrow shows a building roof where the photogrammetric measurement differs by 1·40 m (on average) from the verification data. Here a gable roof was mistakenly interpreted as a flat roof. In Fig. 9(b) 14 dormers were omitted in the 3D building model, shown as red arrows. This deficiency can easily be detected by this approach, which is referred to the completeness criteria.

## Conclusions

Two-dimensional city maps are rapidly being replaced by 3D city models. While the general emphasis has been to develop methods and tools for automatic, or semi-automatic, generation of city models, the concept of quality evaluation has also gained high importance. No standard solutions are available as yet, although city models are being produced worldwide at a remarkable rate.



(a) (b)

FIG. 9. (a) A zoom-in to the central part of Fig. 8(b), in oblique view. The red arrow shows a building with large differences between the model and the point cloud. (b) A zoom-in to the lower-left part of Fig. 8(b), in oblique view. The missing dormers (indicated by the red arrows) can easily be identified by the LS3D surface matcher. 

This paper proposes a quality control method based on 3D surface comparison, together with the development of GUI-based software. The method can process the data within a reasonable time. The most computationally complex portion of the method is the search for the correspondence elements between the verification data and the input model data. A rapid space-partitioning method is used to constrict the search domain.

The method can assess 3D building data in terms of:

(a) systematic errors: errors due to differences between the coordinate systems of the input and verification data-sets and measurement errors of the individual buildings,
(b) gross errors: type I errors (relevant to the completeness), and
(c) random errors: errors due to sensor noise.

Since the lidar point cloud is an unstructured data type, absence (or existence) of an entire building cannot be detected. In the experiments presented here, type I errors address the completeness of integral parts of a building, if the building exists in the input building model. The method cannot identify entirely missing buildings, it can only assess the completeness of building components such as chimneys and dormers (see examples in test sites AV and BO2).

In the current implementation, the method cannot automatically locate the missing model parts, rather it highlights the large residuals in a GUI screen (see Figs. 3(b) and 9(b)). The operator performs the interpretation. This feature will be automated in a future study.

Furthermore, the lidar data contains points belonging to irrelevant objects (ground, vegetation, etc.). These spurious points are detrimental to the procedure. This problem can be solved by using structured data (in surface form) as the verification data-set, instead of lidar point clouds. On the other hand, lidar data can be generated rapidly, which is especially useful in scenarios where the detection of changes in buildings due to settlement activities, or due to natural hazards, is a concern.

Experiments have been carried out on three test sites in Great Britain. The results of this work provide measures of how well an entire building model matches reality and thus helps to identify where it differs. This method, in combination with lidar point clouds as verification data, allows frequent and effortless quality control of 3D building models. This also allows the identification of areas of 3D models requiring update, in order to create high quality and complete 3D city models.

This work focuses on the quality control of 3D building data; however, the same procedure can be used for building change detection.

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## References

Ackermann, F., 1984. Digital image correlation: performance and potential application in photogrammetry. *Photogrammetric Record*, 11(64): 429–439.

Akca, D., 2007. *Least squares 3D surface matching*. Doctoral thesis, Institute of Geodesy and Photogrammetry, ETH Zurich, Switzerland, Mitteilungen Nr. 92. Dissertation No. 17136. 78 pages. http://www.photogrammetry.ethz.ch/general/persons/devrim_publ.html [Accessed: 20th June 2009].

Akca, D., 2010. Co-registration of surfaces by 3D least squares matching. *Photogrammetric Engineering & Remote Sensing*, 76(3): 307–318.

Akca, D. and Gruen, A., 2005. Fast correspondence search for 3D surface matching. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36(3/W19): 186–191.

Akca, D., Gruen, A., Freeman, M. and Sargent, I., 2009. *Fast quality control of 3D city models*. International LiDAR Mapping Forum (ILMF 09), New Orleans, Louisiana, USA. 10 pages (on CD-ROM). http://www.photogrammetry.ethz.ch/general/persons/devrim/2009US_Akca_et_al_OS_ILMF'09_NewOrleans.pdf [Accessed: 21st August 2010].

Ameri, B., 2000. Feature based model verification (FBMV): a new concept for hypothesis validation in building reconstruction. *International Archives of Photogrammetry and Remote Sensing*, 33(B3): 24–35.

Baltsavias, E. P., 2004. Object extraction and revision by image analysis using existing geodata and knowledge: current status and steps towards operational systems. *ISPRS Journal of Photogrammetry and Remote Sensing*, 58(3–4): 129–151.

Baltsavias, E. P., Gruen, A. and Van Gool, L. (Eds.), 2001. *Automatic extraction of man-made objects from aerial and space images (III)*. A. A. Balkema, Rotterdam, the Netherlands. 415 pages.

Baltsavias, E. P. and Gruen, A., 2003. Resolution convergence—a comparison of aerial photos, LIDAR and IKONOS for monitoring cities. Chapter 3 in *Remotely Sensed Cities* (Ed. V. Mesev). Taylor & Francis, London. 433 pages: 47–82.

Boudet, L., Paparoditis, N., Jung, F., Martinoty, G. and Pierrot-Deseilligny, M., 2006. A supervised classification approach towards quality self-diagnosis of 3D building models using digital aerial imagery. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36(3): 136–141.

Capstick, D., Heathcote, G., Horgan, J. and Sargent, I., 2007. Moving towards 3D: from a National Mapping Agency perspective. *Cartographic Journal*, 44(3): 233–238.

Durupt, M. and Taillandier, F., 2006. Automatic building reconstruction from a digital elevation model and cadastral data: an operational approach. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36(3): 142–147.

Elberink, S. O. and Vosselman, G., 2007. Quality analysis of 3D road reconstruction. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36(3/W52): 305–310.

Gruen, A., 1985. Adaptive least squares correlation: a powerful image matching technique. *South African Journal of Photogrammetry, Remote Sensing and Cartography*, 14(3): 175–187.
Gruen, A., 2001. Cities from the sky—photogrammetric modeling of CyberCity is coming of age. *GeoInformatics*, 4(10): 30–33.
Gruen, A. and Akca, D., 2005. Least squares 3D surface and curve matching. *ISPRS Journal of Photogrammetry and Remote Sensing*, 59(3): 151–174.
Grün, A., 2000. Semi-automated approaches to site recording and modeling. *International Archives of Photogrammetry and Remote Sensing*, 33(B5/1): 309–318.
Henricsson, O. and Baltsavias, E., 1997. 3D building reconstruction with ARUBA: a qualitative and quantitative evaluation. *Automatic Extraction of Man-Made Objects from Aerial and Space Images II* (Eds. A. Gruen, E. P. Baltsavias & O. Henricsson). Birkhäuser Verlag, Basel. 393 pages: 65–76.
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. and Shufelt, J. A., 2000. Performance evaluation for automatic feature extraction. *International Archives of Photogrammetry and Remote Sensing*, 33(B2): 379–394.
Meidow, J. and Schuster, H.-F., 2005. Voxel-based quality evaluation of photogrammetric building acquisitions. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36(3/W24): 117–122.
Pertl, A., 1984. Digital image correlation with the analytical plotter Planicomp C100. *International Archives of Photogrammetry and Remote Sensing*, 25(3B): 874–882.
Rottensteiner, F., 2006. Consistent estimation of building parameters considering geometric regularities by soft constraints. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 34(3): 13–18.
Rottensteiner, F. and Schulze, M., 2003. Performance evaluation of a system for semi-automatic building extraction using adaptable primitives. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 34(3/W8): 47–52.
Sargent, I., Harding, J. and Freeman, M., 2007. Data quality in 3D: gauging quality measures from users' requirements. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36(2/C43): 8 pages (on CD-ROM). http://www.isprs.org/proceedings/XXXVI/2-C43/www.itc.nl/issdq2007/proceedings/Session%205%20Dissemination%20and%20Fitness%20for%20Use/paper%20Sargent.pdf [Accessed: 3rd August 2010].
Schuster, H.-F. and Weidner, U., 2003. A new approach towards quantitative quality evaluation of 3D building models. *ISPRS Commission IV Joint Workshop on Challenges in Geospatial Analysis*, Stuttgart, Germany. 8 pages (on CD-ROM). Also ISPRS WG III/8. 6 pages. http://www.ipb.uni-bonn.de/uploads/tx_ikgpublication/schuster03.evaluation.pdf [Accessed: 23rd August 2010].
Suveg, I. and Vosselman, G., 2002. Mutual information based evaluation of 3D building models. *16th International Conference on Pattern Recognition (ICPR)*, Quebec City, Canada, 3. 1043 pages: 557–560.

## *Résumé*

*De nos jours, les modèles de bâtiments en 3D sont très souvent produits à partir de données lidar et photogrammétriques. Le contrôle de qualité de ces modèles est une question pertinente, autant d'un point de vue scientifique que pratique. Cette étude présente une méthode de contrôle de qualité pour ce type de modèle. Le modèle en entrée (représentant les bâtiments en 3D) est apparié aux données de vérification grâce à une méthode d'appariement de surfaces en 3D. L'appariement de surfaces en 3D évalue les distances euclidiennes entre les données de vérification et les données en entrée. Les distances euclidiennes fournissent une mesure adéquate de la qualité des modèles 3D. Elles sont indépendantes de la méthode de relevé des données. La méthode proposée renseigne sur la précision du système de référence, la précision géométrique et l'exhaustivité. Trois exemples pratiques sont présentés pour la démonstration de la méthode.*

*Zusammenfassung*

*3D Gebäudemodelle werden heutzutage häufig aus lidar und photogrammetrischen Daten erzeugt. Die Qualitätskontrolle dieser Modelle spielt unter wissenschaftlichen und praktischen Aspekten eine wichtige Fragestellung. Diese Arbeit präsentiert eine Methode für die Qualitätskontrolle solcher Modelle. Das Input Modell (3D Gebäudedaten) ist ko-registriert zu den Referenzdaten unter Verwendung eines Verfahrens zur 3D Oberflächenzuordnung. Die 3D Oberflächenzuordnung evaluiert die Euklidische Distanz zwischen den Referenzdaten und dem Input Datensatz. Die Euklidische Distanz gibt eine geeignete Metrik für die 3D Modellqualität. Diese Metrik ist unabhängig von der Methode der Datenerfassung. Die vorgestellte Methode geht auf die Genauigkeit des Referenzsystems, die Positionsgenauigkeit und die Vollständigkeit ein. Drei praktische Bespiele werden vorgestellt, die die Methode verdeutlichen.*

*Resumen*

*En la actualidad los modelos tridimensionales de edificaciones se generan a menudo a partir de datos fotogramétricos y lidar. El control de calidad de estos modelos es una cuestión relevante desde los puntos de vista científico y práctico. Este trabajo describe un método de control de calidad de los modelos. El modelo de entrada (datos tridimensionales de edificaciones) se corregistra con los datos de verificación empleando un método de ajuste de superficies tridimensionales. Este ajuste evalúa las distancias euclídeas entre los conjuntos de datos de verificación y de entrada. Las distancias euclídeas proporcionan una medida apropiada de la calidad del modelo tridimensional. Esta medida es independiente del método de obtención de datos. El método propuesto puede resolver de forma adecuada la exactitud del sistema de referencia, la exactitud posicional y la completitud. Como demostración se aportan tres ejemplos prácticos de aplicación del método.*