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QUALITY ASSESSMENT OF 3D BUILDING DATA

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Abstract

3D building models are often now produced from LIDAR and photogrammetric data. The quality control of these models is a relevant issue both from scientific and practical points of views. 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: Quality assessment, 3D building model, LIDAR, point cloud, surface co-registration, 3D comparison

INTRODUCTION

FOR about 20 years 3D city modelling has been an important issue in R&D. Many different techniques have been proposed, especially for reality-based concepts. Reviews can be found in Mayer (1999), Gruen (2000), Baltsavias et al. (2001), Baltsavias and Gruen (2003) and Baltsavias (2004). 3D 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 (satellites, aerial – surveying aircraft, UAVs, terrestrial – mobile mapping, street images).

While the methods for generating virgin datasets efficiently and reliably are still being developed and optimized, little has been done with respect to the quality control of these data and the updating/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). Qualitative and visual evaluation based methods 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 last few years, Ordnance Survey 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 (Sargent et al., 2007; Capstick 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. The metrics and methods should correspond to customers’ requirements (of Ordnance Survey) and should be independent of the method of data capture. The outcomes of the project are presented in this paper.

This work designs a quality assessment method that have practical meaning to users, so as to ensure that data are captured according to users’ requirements and that users understand the quality of the 3D data for their purposes. 3D building data are in 3D surface model form. For that, the existing pixel or voxel based representations are only indirect approaches and thus sub-optimal. 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 re-sampling errors. The advantage of our methodology is treatment of the problem in 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 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 next chapters introduce the 3D surface matcher and the quality assessment strategy. When the ALS point clouds are used as the reference, irrelevant points (points belong to terrain, vegetation, etc.) should be excluded. Details of a filtering process using the SCOP++ LIDAR software are given in the fourth chapter. The results of the experiments conducted at three test sites in the UK are shown in the fifth chapter.

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 generalization 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 Generalized Gauss-Markov model, minimizing 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 give 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; Akca, 2010).

Correspondence search

For every surface element of the verification data, the correspondence operator seeks a location 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 TIN (Triangulated Irregular Network) 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 a 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 3D building data quality assessment case, 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 28-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 localize and eliminate outliers and occluded parts. During the iterations, a simple weighting scheme, adapted from robust estimation methods, is used:

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

where vector $(\boldsymbol{v})_i$ 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 ≥ 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 ≥8 or 10, the computation is usually distorted by the impairing effect of the non-relevant points, i.e. points belonging to ground or trees, etc.

QUALITY ASSESSMENT STRATEGY

Without restricting the generality of the approach it is assumed that the verification data are given as LIDAR point clouds and the input building model data are 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 both 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 factorized 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 both data sets. The rotational and scale differences are not significant. Then, the LS3D algorithm is run in the 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) 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, or surfel, element 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 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 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 one get quality measures. 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 sorts of gross error (or outlier), which are 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 is the criteria for the completeness, describes the rejected or missing buildings (partially or entirely). This means in the presented methodology that some elements of the verification data will not have any correspondence with the input data. Unfortunately, completeness of the entirely missing buildings can not be detected, since the LIDAR point cloud (as verification data) is unstructured. Our methodology can only assess the completeness of sub-building parts, e.g. 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 Fig. 3(b) and 9(b)), thereby it assists 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. The SCOP++ LIDAR classifies the LIDAR point clouds into 7 classes: ground, below (outlier points below the ground), building, high vegetation, medium vegetation, low vegetation, and unclassifiable. Among them the classes ground, below and low vegetation

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, the 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 to the verification point cloud to ensure the completeness of the buildings.

EXPERIMENTAL WORK

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

a) Avonmouth test area (AV),
b) Bournemouth test area 1 (BO1),
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/m2 density and were delivered in both ENZI and LAS formats. The LIDAR point clouds were used as verification data in all experiments.

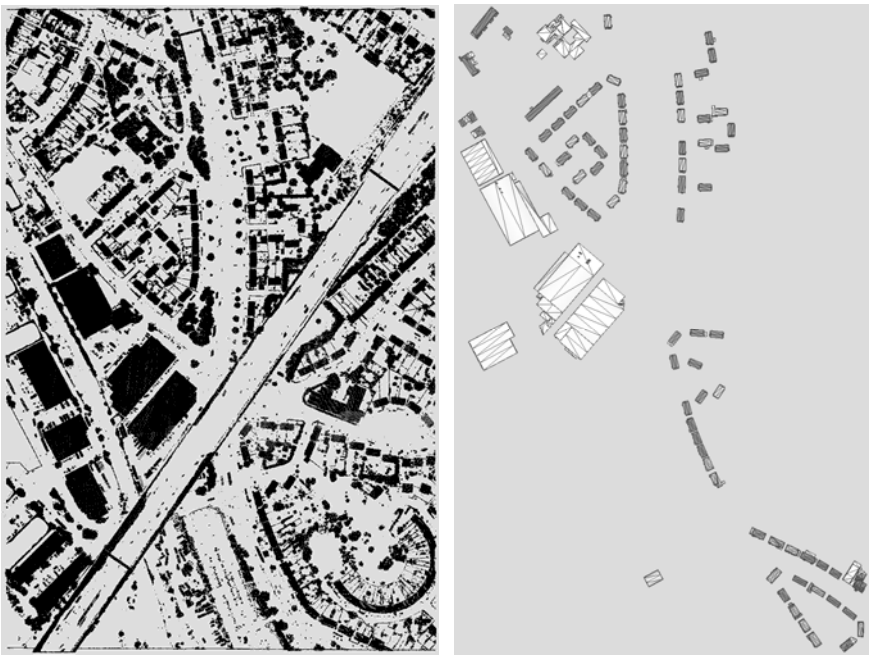
The 3D buildings were captured using stereo pairs of DMC (Intergraph) images from a nadir block with 60% overlap and sidelap. The low resolution RGB imagery was pan-sharpened with the high resolution panchromatic image, resulting in imagery with a GSD of approximately 15cm (flying height around 1500-1600 m, focal length 120 cm, and pixel size 12 microns). The building measurements were gathered using CC-Modeler software (CyberCity 3D, Inc., El Segundo, CA, USA) in semi-automatic mode by a photogrammetry 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 a 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 4 721 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 (sigma naught a posteriori) before the LS3D surface matching is 0.77 m (Table 1). 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, e.g. points on the terrain, trees and bushes etc.



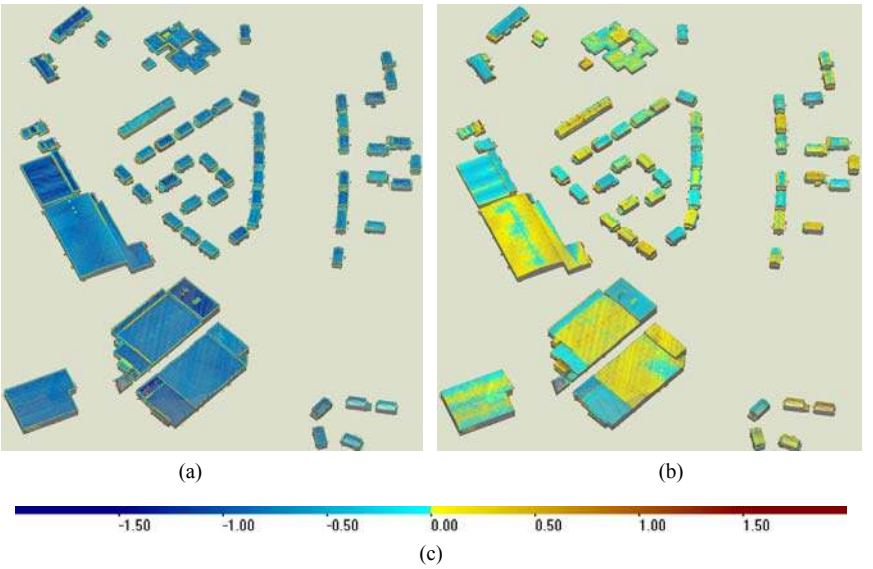
(a) (b)

FIG. 1. Avonmouth test site. (a) Filtered LIDAR point cloud, (b) 3D building model data. Ordnance Survey © Crown copyright. All rights reserved.

TABLE 1. Processing results of test site AV.

Step	*No. of corres.*	*No. of iter.*	*Time (min.)*	$\hat{\sigma}_0$ *(m)*	*Tx (m)*	*Ty (m)*	*Tz (m)*	*Stdd-Tx (m)*	*Stdd-Ty (m)*	*Stdd-Tz (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

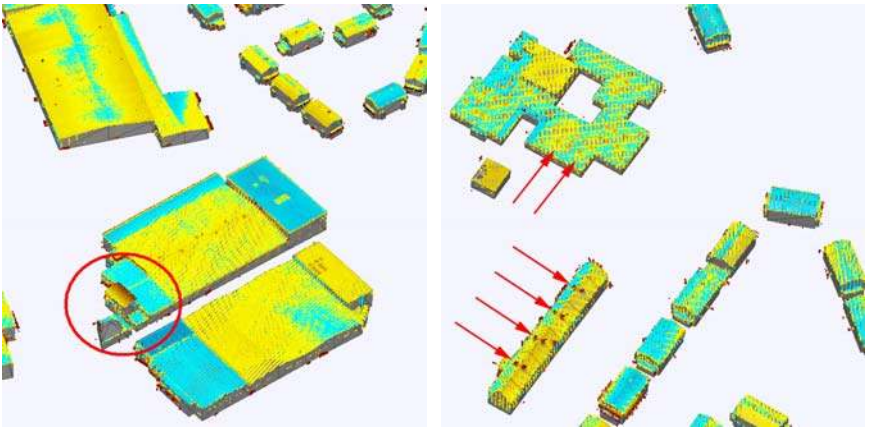
No. of corres. : Number of correspondences.
No. of iter. : Number of iterations.
$\hat{\sigma}_0$: Standard deviation of the Euclidean distances a posteriori.
Tx : *X* component of the estimated translation vector.
Ty : *Y* component of the estimated translation vector.
Tz : Z component of the estimated translation vector.
Stdd-Tx : Theoretical precision of the *X* component of the estimated translation vector.
Stdd-Ty : Theoretical precision of the *Y* component of the estimated translation vector.
Stdd-Tz : Theoretical precision of the *Z* component of the estimated translation vector.



(a) (b)

(c)

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



(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. Ordnance Survey © Crown copyright. All rights reserved.

Step 2. The robust weighting factor is set to 4 times of the sigma naught (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, –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) to 2(b). This reference system error is eliminated by applying the estimated translation vector to the 3D building data (Table 1).

Step 3. After correcting the reference system errors, the sigma naught dropped down 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 (b)) are due to non-relevant (disturbing) terrain points which the LS3D surface matcher considers to be part the buildings due to their proximity. Thus, the sigma naught 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, as 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. They are again likely omitted by the photogrammetry operator.

As seen in Table 1, changing the robust weighting factor affects the number of correspondences found and consequently the sigma naught a posteriori. In Step 2, the robust weighting factor is 1.16 m (4 times of the sigma naught of the current iteration, equivalent to 4 x 0.29 m = 1.16 m in the last iteration). In Step 3, it was increased to 2.00 m, resulting in more correspondences than Step 2, and accordingly, a slight increase (1 cm) in the sigma naught a posteriori.

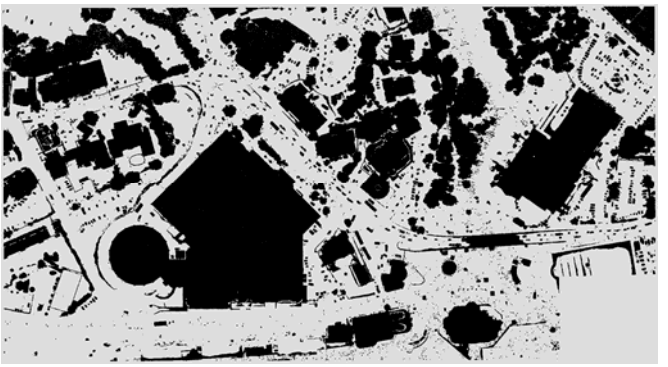
Results of test site BO1

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 8 153 triangles. The scene contains, apart from the others, a large building with complex roof structures (Fig. 4(b)).

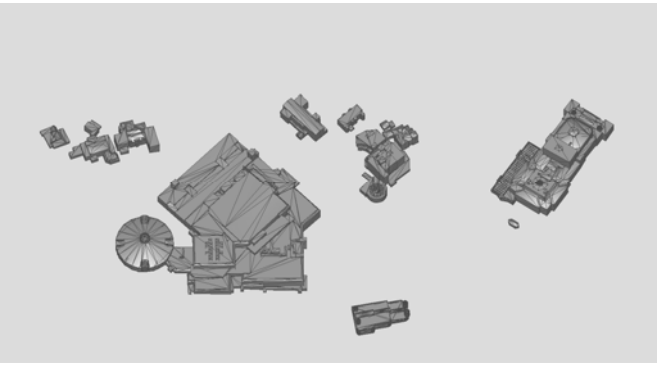
Step 1. Standard deviation of the Euclidean distances before the LS3D surface matching is 0.49 m (Fig. 5(a) and Table 2). The computation takes 11.2 minutes for 1 445 568 correspondences.

Step 2. The robust threshold value is set to 4 times of the sigma naught (of the current iteration). The translational reference system difference between the model building data and the verification LIDAR data is +0.11, –0.23, +0.03 m for the *X*, *Y* and *Z* axes, respectively (Table 2). In contract to test site AV, here the two reference systems differ along the horizontal direction only, but not along the vertical direction significantly.

Step 3. The sigma naught a posteriori 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 neglectable as 1 cm.



(a)



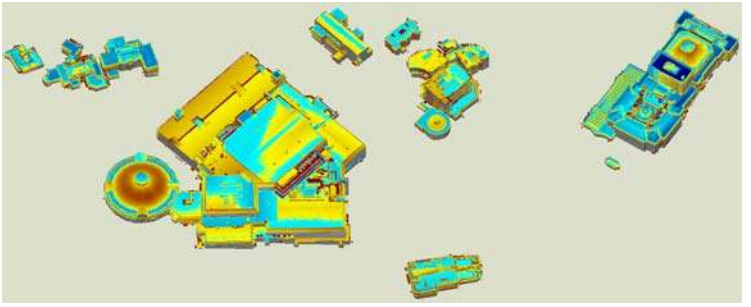
(b)

FIG. 4. Test site BO1. (a) Filtered LIDAR point cloud data, (b) 3D building model data. Ordnance Survey © Crown copyright. All rights reserved.

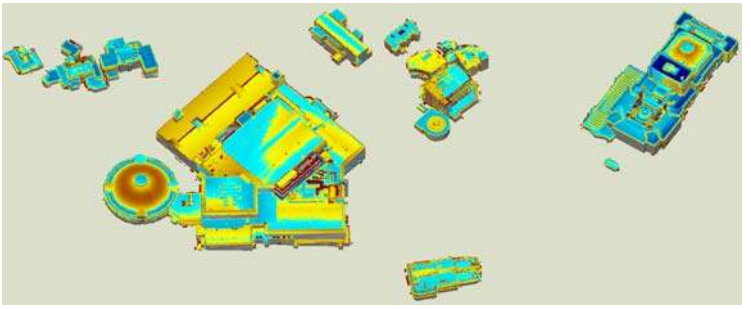
TABLE 2. Processing results of test site BO1.

Step	*No. of corres.*	*No. of iter.*	*Time (min.)*	$\hat{\sigma}_0$ *(m)*	*Tx (m)*	*Ty (m)*	*Tz (m)*	*Stdd-Tx (m)*	*Stdd-Ty (m)*	*Stdd-Tz (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

The test site exhibits two interesting measurement error examples. 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 meters 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 meters.



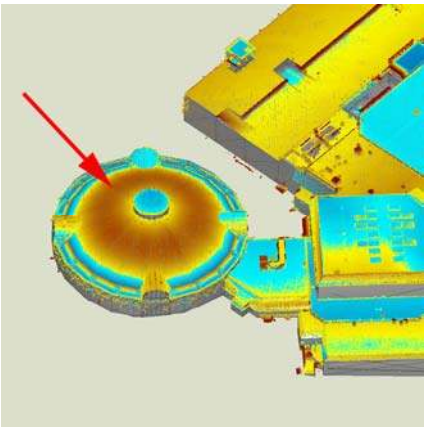
(a)



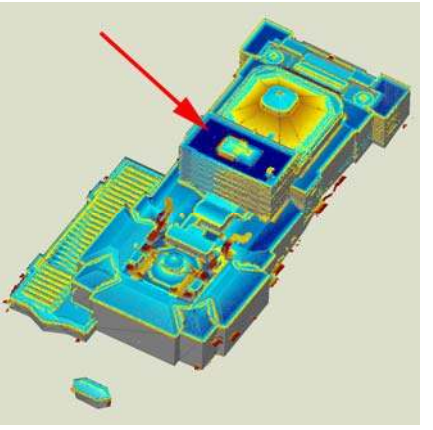
(b)

(c)

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 meter units. Ordnance Survey © Crown copyright. All rights reserved.



(a)



(b)

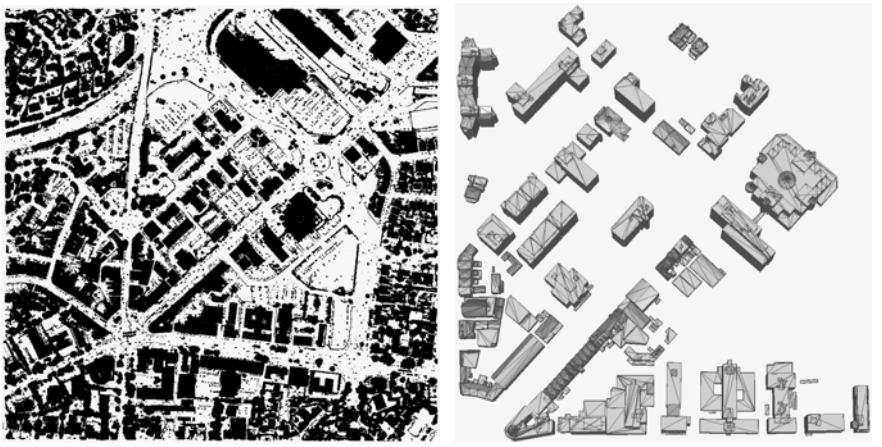
FIG. 6. (a) A zoom-in to the lower left part of Fig. 5(b). (b) A zoom-in to the upper part of Fig. 5(b). The red arrows in (a) and (b) show a dome and a roof with large deviations from the verification point cloud data. Ordnance Survey © Crown copyright. All rights reserved.

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 6 279 triangles.

Step 1. The standard deviation of the Euclidean distances before the LS3D surface matching is 0.65 m (Table 3). The algorithm computes 999 938 Euclidean distances in 5.3 minutes. 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 of the sigma naught (of the current iteration). The translational reference system difference between the building model data and the verification LIDAR data is +0.24, –0.24, –0.49 m for the *X*, *Y* and *Z* axes, respectively (Table 3). Both horizontal and vertical components of the translation vector show numerically significant differences between the two reference systems.



(a) (b)

FIG. 7. Test site BO2. (a) The filtered LIDAR data, (b) the 3D building data. Ordnance Survey © Crown copyright. All rights reserved.

TABLE 3. Processing results of test site BO2.

Step	*No. of corres.*	*No. of iter.*	*Time (min.)*	$\hat{\sigma}_0$ *(m)*	*Tx (m)*	*Ty (m)*	*Tz (m)*	*Stdd-Tx (m)*	*Stdd-Ty (m)*	*Stdd-Tz (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

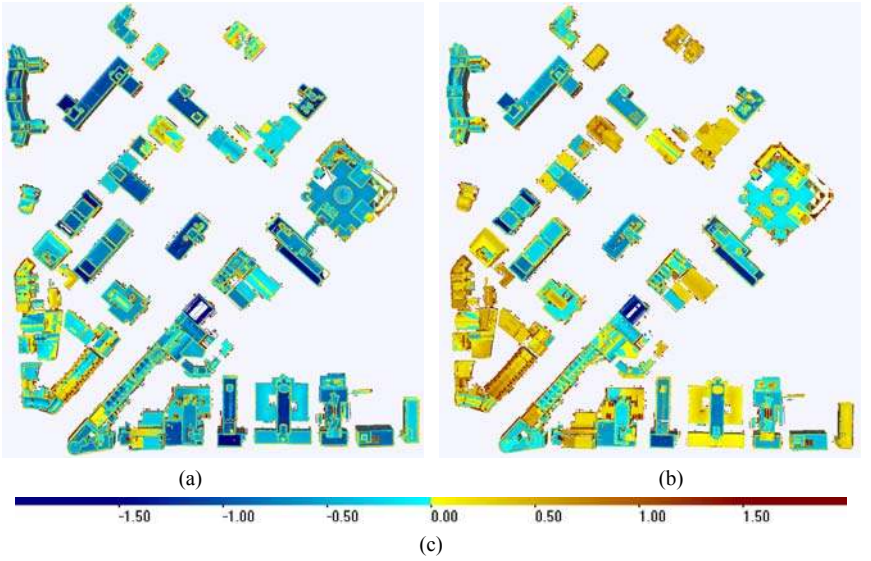


FIG. 8. (a) Test site BO2 before LS3D surface matching. (b) Test site BO2 after LS3D surface matching (the errors due to the reference system differences are now corrected). (c) Residual bar in meter units. Ordnance Survey © Crown copyright. All rights reserved.

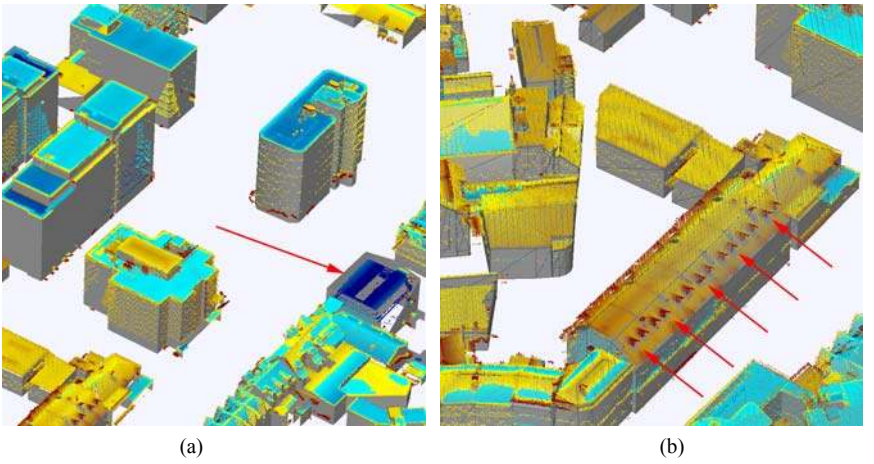


FIG. 9. (a) A zoom-in to the central part of Fig. 8(b), in oblique view. The red arrow shows a building with large differences between the model and the point cloud. (b) A zoom-in to the lower-left part of Fig. 8(b), in oblique view. The missing dormers (indicated by the red arrows) can easily be identified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

The change of the coloured residuals from Fig. 8(a) to 8(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 factorization of the reference system and measurement errors from each other.

Step 3. The sigma naught at this step is 0.54 m. The robust threshold value is 2.00 m again. See Fig. 8(b), 9(a) and 9(b) for the graphical results. From Step 1 to Step 3, the gain is 11 cm in terms of sigma naught (Table 3). 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 Fig. 8(b) and 9(a).

In Fig. 9(a) the arrow shows a building roof where the photogrammetric measurement differs 1.40 m (on average) than the verification data. Here a gable roof was mistakenly interpreted as a flat roof. In Fig. 9(b) fourteen dormers were omitted in the 3D building model, shown as red arrows. This deficiency can easily be detected by our approach, which is referred to the completeness criteria.

CONCLUSIONS

2D city maps are rapidly been replaced by 3D city models. While the general emphasis has been to develop methods and tools for automatic, or semi-automated, 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 produced world-wide at a remarkable rate.

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 correspondent 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 can not be detected. In the presented experiments, type I errors address the completeness of integral parts of a building, if the building exists in the input building model. Our method cannot identify entirely missing buildings, it can only assess the completeness of building subparts, e.g. 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 Fig. 3(b) and 9(b)). The operator performs the interpretation. This feature will be automatized 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 dataset, instead of LIDAR point clouds. On the other hand, LIDAR

data can be generated rapidly, which is especially useful in scenarios where the change detection of buildings due to settlement activities, or due to natural hazards, is a concern.

Experiments have been carried out on three test sites in the UK. The results of our 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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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. Les données en entrée (des données de bâtiments en 3D) sont appariées aux données de vérification grâce à une méthode d'appariement de surfaces en 3D. La méthode d'appariement de surfaces en 3D évalue les distances euclidiennes entre les données de vérification et les données en entrée. Les distances

euclidiennes sont des mesures adéquates pour décrire la qualité du modèle 3D. Elles sont indépendantes de la méthode de relevé des données. La méthode proposée renseigne sur la précision du système de référence, la précision géometrique 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 kann die Genauigkeit des Referenzsystems, die Positionsgenauigkeit und Vollständigkeit untersuchen. Drei praktische Bespiele werden vorgestellt, die die Methode verdeutlichen.