Automated Registration of Building Scan with BIM through Detection of Congruent Corner Points

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ABSTRACT:

Current methods of construction progress monitoring involve manual data collection and processing, which are time-consuming and labor-intensive, with a dominant human presence entailing several flaws such as missing or inaccurate information. Recent research efforts for automated progress monitoring have largely focused on model-based assessment methods that are dependent on a pre-requisite step known as registration which is still performed manually due to numerous challenges. This study proposes a novel automated coarse registration method that utilizes the BIM model as the as-planned model to align it with the corresponding as-built model using their geometrical features. First, it extracts the corner points in both models using their planar features and then identifies the conjugate corner points based on different geometric invariants. Later, the transformations are determined from those conjugate points and the most accurate transformation parameter is finalized in the end. The proposed method is validated on different datasets.

1. INTRODUCTION

Current progress monitoring is based on manual methods that are time-consuming, labor-intensive, and subject to human interpretation, therefore, demands an automated and accurate monitoring method [1-3]. Many studies to automate the progress monitoring have been investigated that performed Scan-vs-BIM in which the scan model of the building is compared with its Building information model (BIM) model. The scan model is usually obtained through three-dimensional (3D) reconstruction technologies such as laser scanning, image-based reconstruction, or integration of both. Similarly, the BIM model is utilized as the as-planned model to represent the geometrical and semantic information of the building. The Scan-vs-BIM results in the differences between both models that are interpreted to provide progress information. However, effective progress monitoring in this way demands accurate alignment of scan and BIM models. The alignment is performed through a registration step.[4-6].

Registration is a widely researched topic with most focused on the alignment of different point clouds of the same scene. In comparison, registration of BIM with its scan model, as as-planned and as-built model respectively, is not so actively studied. Normally, registration is performed in a coarse-to-fine (global-to-local) strategy where coarse registration roughly aligns the models that are later made accurate using fine registration. Fine registration, mostly performed with a well-established iterative closest point (ICP) algorithm, is dependent on the success of coarse registration. In coarse registration, the extraction of quality geometric features from both models and then finding their congruent pairs to compute the transformation parameter is critical and remains the area of challenge. Coarse registration approaches employing the planar features are usually less effect by outliers and they are more robust in finding the conjugate features [7,8]. As the building structures are enriched with dominant planar features, therefore, plane-based approaches can be a suitable solution for their registration. Hence, many studies utilized these approaches and proposed different methods; however, these methods faced some challenges including the lack of discriminatory features and distinct invariants for reliable congruent detections.

The proposed research presents a novel method to extract and find the congruent match of discriminatory corner points from models to solve the registration problem for Scan-vs-BIM. The method extracts the corner points from both models from the combination of planar features and then assesses them through a pruning strategy using different geometric criteria to find the potential congruent pairs along with their transformation parameters. Later, the congruent corner points are identified from the potential points and then the optimal transformation is computed.

The remainder of this paper is structured as follows. The related work is presented in section 2. The detailed methodology is described in section 3. Experimentation of the proposed method along with the results is presented in section 5. Finally, the conclusions are outlined in Section 6.

2. RELATED WORKS

Registration, referred to as the alignment of different models or scenes according to the congruent geometrical information, has been extensively studied. It is achieved by estimating the rotation and translation parameters between the congruent features. Generally, existing fine registration can accurately perform registration, however, they require some good initial registration that is achieved through coarse registration techniques, hence, a coarse-to-fine registration strategy is adopted [9]. Fine registration is already well-established due to its mainstream techniques including the popular ICP algorithm [10] and its variants [11-13]. However, coarse registration is still facing numerous challenges and many attempts have been made to address the challenges.

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Generally, coarse registration adopts the feature-based approach where the registration is performed based on the geometric features present in the models. This approach is widely accepted due to the substantial presence of geometric characteristics in the models or scenes. The main steps involved are the extraction of geometric features from models and then detection of the congruent features to compute the transformation. The extraction of geometric features requires the selection of key points or primitives formed from points and their utilization, instead of entire 3D points in the model, in the registration process eases the computation and improves the congruency detection [14]. These geometric features are constructed from geometric characteristics such as fast point feature histograms (FPFHs) [15], intersecting lines [16], planes [17], patches [18], curves [19], or semantic feature lines [20]. Likewise, the techniques that detect the congruent features include Random sample consensus (RANSAC) [21], geometric consistency constraints [22], inliers search [23], fast matching pruning (FMP) [24].

According to the type of features, coarse registration can be categorized into point-based or primitive-based. The point-based approaches such as SIFT key points [25,26], virtual intersection points [27], FPFH key points [28], SURF key points [29], and semantic feature points[20,30] have performed the registration of point clouds, however, their success is affected by noise and varying point density and large datasets can reduce their efficiency[31]. In comparison to points, primitive-based approaches use line, plane, or curved surface as features proved to be more robust in detecting the congruent features [14]. Some studies employed the line feature as linear invariant [32,33], as the meeting of adjoining planes [16] and footprint from building [34] for registration. Curved surfaces [18] are also studied as the congruent feature to compute the transformation. Furthermore, the planar surfaces are also used in many studies [6,7,17,31,35-38] as a geometric feature. These plane-based approaches performed well particularly in urban infrastructures due to the presence of considerable planar features in the urban structures [9].

Buildings have plentiful dominant planar features and utilizing those features, instead of all the 3D geometrical elements, can reduce the overall computation. Similarly, the plane-based registration approaches are not much affected by outliers present at the construction site, therefore, they can enhance the overall accuracy [7]. These approaches are dependent on the quality of extracted planes. The planes are extracted from points clouds using the segmentation techniques that include RANSAC segmentation [39-41], region growing [42], voxel-based growing[31], Hough transform [43], and dynamic clustering [38]. Many researchers performed registration using the geometric information acquired from the set of three planes. Dol and Brenner [35] performed the search using the tripe product of plane normal to find their congruent pairs. The search process ended with the acceptable outcome in which the combinatory complexity was lowered using several geometrical constraints including the area, bounding length, and mean intensity values but the practical details were not published [8]. Likewise, Brenner, et al. [44] utilized the angles between the three planes for congruency. Theiler and Schindler [27] approached the congruency problem by extracting the virtual tie points computed from the three planes using the descriptors based on geometrical characteristics of planes in which the distance within the tie points is used as the congruency invariant. To reduce the combinatory complexity, candidates were restricted using a specific threshold. However, this method didn't address the additional tie points from the non-intersecting planes that may be generated at symmetrical distances. Similarly, the utilization of only distance constraints may not be reliable to find congruent pairs. Furthermore, the success rate was also affected by occlusion and high noise. In [31], the congruency problem was approached through a coordinate frame computed from the normal values of three planes through a RANSAC-based strategy. In each iteration, transformation parameters from the corresponding coordinate frame of planes were obtained and then assessed according to the no. of coplanar patches. In the end, transformation with the highest coplanar patches is finalized. In the case of models with many parallel planes, this method may end up with incorrect transformation parameters due to the utilization of only coplanar criteria. Furthermore, Li, Gao, Wang and Li [38] introduced a registration method with two strategies that find the set of three congruent planes intersecting at a point based on their relative angles. The first strategy finds the congruency between those set of planes having different relative angles with each other. In the case of non-availability of plane sets with all different relative angles, the method utilizes the second strategy that congruency between the sets having at-least one perpendicular relative angle. This method may also fail if there are too many planes because the utilization of only angle constraints makes it unreliable. Kim, et al. [45] proposed the plane-congruency algorithm that compares the normal values in the set of three planes to find their congruent pairs. The algorithm computed the rotation matrix from the direction of congruent planes and translation is calculated from the tie points of congruent planes. This study utilizes the algorithm as the second choice if the primary method is not sufficiently aligned based on the features of the RGB-fused point cloud. This method didn't describe the congruency process nor the transformations were verified through any evaluations. Besides the limitation of all these mentioned methods, neither of them performed the registration in the context of construction progress monitoring that involves Scan-vs-BIM.

In studies addressing the Scan-vs-BIM problem, Kim, et al. [46] utilized a coarse-to-fine strategy to register the as-built point cloud with the as-planned point cloud converted from CAD model. The coarse registration employed the Principal component analysis (PCA) [47] in which the rotation was computed from the bases formed by principal components of models and the translation was computed from the centroids of models. This practicality of this method is limited in real-life scenarios that include the noise and occlusions because it is assumed that both models have the same congruent centroid with principal components of both models having the same directions. These two assumptions are only valid if both models are exactly the same. Although the aforementioned studies offer various solutions, however, the registration of building models particularly in the Scan-vs-BIM problem is still a challenge due to the lack of discriminatory features and distinct invariants for congruency detection.

3. METHODOLOGY

The proposed method involves three major steps that are explained as follow:

3.1 Extraction of corner points

The extraction of corner points from the models is performed using their plane models. Initially, both the models are pre-processed to obtain their best form. The scan model, referred to as the as-built model, is down sampled using voxelization with a suitable voxel size to ease the computation and remove the uneven distribution of points. After that, plane segmentation is performed to acquire the plane segments from the as-built model. In the case of BIM, referred to as the as-planned model, it can be converted into the point cloud or other suitable format for compatible comparison with the as-built model. As the conversion results in loss of quality in geometrical parameters, therefore, the required geometrical information (including the vertices and faces) of vertical and horizontal structural building elements (such as wall, roof, slab) are directly extracted from IFC based BIM by traversing the 'Representation' attribute. This geometrical information is then utilized to create accurate meshes that are later used as plane segments.

After obtaining the plane segments from both models, corner points as the unique intersection point between three non-parallel plane segments is computed using the following equation:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} n_a \\ n_b \\ n_c \end{bmatrix}^{-1} \begin{bmatrix} d_a \\ d_b \\ d_c \end{bmatrix} \tag{1}$$

In the above equation, a corner point with coordinates (x, y, z) is calculated from three plane segments having unit normal vectors $(n_a,\ n_b,\ n_c)$ with distance from the origin $(d_a,\ d_b,\ d_c)$ respectively. All the corner points with possible combinations of plane segments are extracted. Similarly, it is ensured that the calculated corner point is intersecting its respective three plane segments with some suitable tolerance as the equation (1) calculates the corner point irrespective of the actual intersection of plane segments with each other. Otherwise, the accuracy and efficiency of the proposed method can be affected in lateral processing due to the inclusion of additional false corner points. An example of corner points extracted from their corresponding is shown in Figure 1.

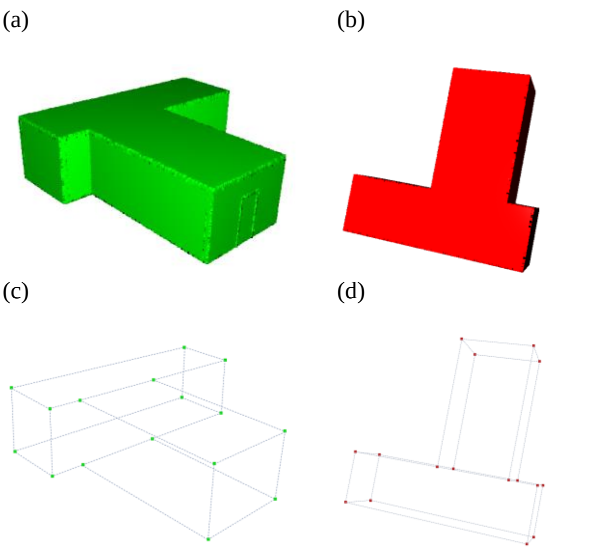

Figure 1. Visualization of corner points (c, d) extracted from their respective models (a, b)

3.2 Assessment of corner points

After extracting the corner points, a step-wise assessment is performed using a pipeline of different geometric criteria to find out the potential congruent points along with their respective transformation parameters. If the as-built model is transformed with rotation matrix $R \in SO(3)$, and translation vector $\boldsymbol{t} \in \mathbb{R}^3$as compared to the as-planned model, then the congruent corner points from these respective models, represented by $\{\boldsymbol{d_i}\}_{i=1}^{N} \in \mathbb{R}^3$and $\{\boldsymbol{m_i}\}_{i=1}^{N} \in \mathbb{R}^3$, satisfy the following equation:

$$a = Rd_i + t \tag{2}$$

Based on that, the congruency of corner points is assessed through a series of different geometric certainties that input two points from both models in each iteration and reject the non-congruent pairs to ultimately filter out the potential congruent points. These assessment steps are explained below:

Initially, the corner points are processed according to the certainty that the distance within two points in both models should be the same if they are congruent. For example, if two transformed corner points from the as-built with rotation R and translation t and their corresponding congruent points from the as-planned model are represented by $\{d_a, d_b\}$ and $\{m_a, m_b\}$. Based on the invariant that both corresponding congruent points have the same translation 't', equation (1) can be written as:

$$m_a - Rd_a \ = \ m_b - Rd_b \tag{3}$$

$$m_a - m_b - R.(d_a - d_b) = 0 \tag{4}$$

As rotation matrix 'R' is independent of Euclidean norm, therefore, the above equation becomes:

$$\|m_a - m_b\| - \|d_a - d_b\| \ = 0 \tag{5}$$

In the above equation, $\|\,.\,\|$ is the Euclidean norm in $\mathbb{R}^3$. This equation enables the mass rejection of non-congruent pairs of corner points without the need to calculate other parameters at this initial stage that ultimately ease the overall computation.

The remaining pairs of corner points are scrutinized based on the certainty that the congruent corner points are computed from the congruent plane segments, therefore, the relative angles between the congruent plane segments belonging to the corresponding corner points should also be equal. If an as-planned corner point m_a and its congruent as-built point d_a are computed from plane segments with normal values $\{n_{m_1}, n_{m_2}, n_{m_3}\}$ and $\{n_{d_1}, n_{d_2}, n_{d_3}\}$ respectively, then the equivalency of relative angles between the plane segments can be compared using their normals (e.g. $\angle \mathrm{n}_{\boldsymbol{m_1}}\mathrm{n}_{\boldsymbol{m_2}} \simeq \angle \mathrm{n}_{\boldsymbol{d_1}}\mathrm{n}_{\boldsymbol{d_2}}$).

Once the non-rejected pairs of two corner points having the same distance and relative angles are obtained, the corresponding transformations of both points are obtained for further scrutiny. The rotation matrix can be calculated using the directions of corresponding plane segments of corner points while the translation is calculated from the corner points. Normally, the planes are perpendicular in building models, consequently, the correspondence of plane segments to find the rotation matrix is not certain due to identical angles between the planes, therefore, the transformation obtained based on those correspondences may not be correct.

To calculate the correct transformation of particular corresponding points, all the potential rotation matrices are first calculated using all the possible correspondences of plane segments and then evaluated based on the certainty that the transformation matrix with correct rotation should fit the congruent plane segments. Therefore, all the possible transformations obtained with the potential rotation matrices are probed using the centroids of plane segments belonging to the corresponding corner points. In the ideal case, the centroids of congruent plane segments should project into each other if transformed with correct rotation, however, due to the presence of noise or occlusion, the projection may fall near. Therefore, all the transformations with the possible rotation matrices are scrutinized with the average centroid of plane segments using the given equation.

$$C_{m_a} - R_r . C_{d_a} - t_r = 0 \tag{6}$$

The transformation matching the planes segments according to above equation is considered as the correct transformation allowing the alignment of correct corresponding plane segments.[as shown in fig]. It is worth mentioning that the obtained transformation is correct according to the two corresponding corner points, however, the congruency of these corresponding points still needs to be probed.

After obtaining the transformation parameter of both pairs of corresponding corner points, they are compared to probe the congruency of the corner points. The comparison is performed based on the invariant that the rotation matrices and the translation vectors obtained of all the congruent corner points should be the same. In our case, transformation parameters of both pairs of corresponding corner points are compared. The equivalency of rotation matrices $\{R_a, R_b\}$ and translation vectors $\{t_a, t_b\}$ obtained from as-planned corner points $\{m_a, m_b\}$ corresponding to as-built corner points $\{d_a, d_b\}$ are ensured using the following equations:

$$R_a . {R_b}^T = I_3 \tag{7}$$

$$\|m_a - R_a . d_a\| - \|m_b - R_b . d_b\| = 0 \tag{8}$$

In the end, the pairs of potential congruent corner points that are compatible with the geometric invariants are acquired. These potential congruent points include the congruent points with correct transformations and non-congruent points as well. Therefore, these potential congruent points are further processed in the coming stage to identify the congruent points with correct transformation. All the assessment steps should be performed with suitable tolerance to scrutinize the potential pairs of corner points.

(a) (b)

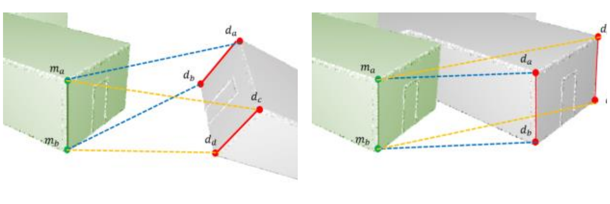

Figure 2. Visualization of pair of as-planned corner points having possible congruency with two pairs of as-built corner points (a) before transformation scrutiny and, (b) after complete geometric assessment.

The figure 2(a) shows an example in which a pair of corner points $\{m_a, m_b\}$ from the as-planned model have more than one potential congruent pairs $\{d_a, d_b\}$ *and* $\{d_c, d_d\}$ in the as-built model due to equal distance and relative plane angles of points. However, figure 2(b) shows that the transformation parameters of non-congruent pair $\{d_c, d_d\}$ was rejected while verifying the computed parameters, as potentially congruent pair $\{d_a, d_b\}$ has the transformation parameters that correspond the centroids of plane segments using equation (6) in contrast to non-congruent pairs. Similarly, the same congruent pair also maintained it congruency while verifying the similarity of transformation parameter computed from individual corresponding points using equation (7) and equation (8).

3.3 Identification of optimal transformation

This stage identifies the congruent points with correct transformation and then finalizes the most accurate transformation among them as optimal transformation. As the assessment process output the pairs of two corner points from both models in each iteration, hence, many pairs may be present more than once, therefore, it is ensured that no congruent points be repeated more than one by confirming their corresponding congruent plane segments.

The identification of congruent points is based on the certainty that the correct transformation parameter should project all the congruent corner points into each other. To do so, all the potential congruent points are clustered according to their respective transformation to obtain the possible cluster each having points with similar transformations. As the cluster of transformations indicates the no. of corner points with potential congruent points transformed with cluster transformation, therefore, transformation with the highest no. of potential congruent points will be finalized as correct transformation following the mentioned certainty.

(a) (b)

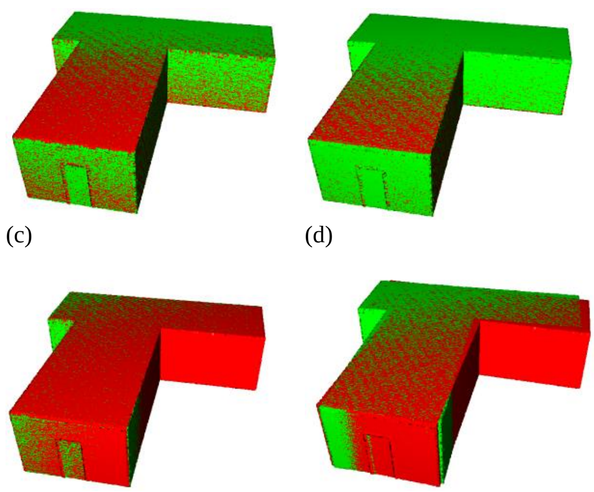

Figure 3. Visualization of models registered with transformation parameters sorted in ascending order from (a) to (d) according to respective errors.

After identifying the cluster of congruent points with correct transformation, the individual transformation parameter of each congruent point is evaluated to find the error in terms of fitting all the congruent points. For example, if d_i and m_i represents the congruent point from as-built and as-planned model at *i*-

correspondence with transformation parameter (R, t) with n number of congruent points, then error (E) can be computed using the given equation:

$$\mathrm{E}(R, t) = \sum_{i=1}^{n} \|(m_i - R.d_i - t)\|^2 \qquad (9)$$

The transformation parameter giving the lowest error is concluded in the end as it is aligning all the congruent points with maximum accuracy. An example of models registration transformation parameters are shown in Figure 3 along with the respective errors where it is evident that the parameter with lowest error is comparatively giving best fitting of models.

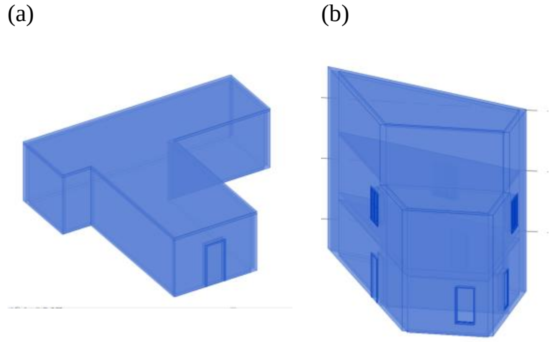

Figure 4. Visualization of as-planned models from (a) dataset 1, and (b) dataset 2.

4. EXPERIMENT

The proposed method was tested on different models including two stimulated and one real building dataset to validate its methodology. Dataset 1 and 2 were artificially prepared stimulated datasets to analyze the proposed methodology with any effect of errors while dataset 3 represented a real-life dataset to assess the working in real conditions. The as-planned model of datasets 1 and 2, representing the single and three floor buildings, are shown in Figure 4. For testing, their random transformed model was used as the as-built model. In the case of dataset 3, the as-planned model and as-built model representing the scan and BIM respectively of a conference room are shown in Figure 5. The as-built model comprised of laser-scanned point cloud having 3,580,303 3D points coupled with noise and occlusion. The proposed method was executed in Python language and testing was performed on a laptop with an Intel i7-8850H CPU and 16 GB RAM.

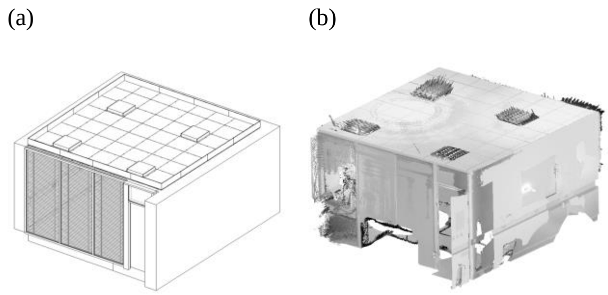

Figure 5. Visualization of (a) as-planned model, and (b) as-built model, from dataset 3

The proposed method successfully performed the registration of BIM with its corresponding scan model after performing all three major steps. The registration results are shown in Figure 6 and the processing details including the time and accuracy of the proposed registration are listed in Table 1. If the accuracy is analyzed that it is evident that the proposed method successfully registered the models with good accuracy in terms of coarse registration. The reliability of the registration can linked to the methodology that finds the potential congruent points from extracted corner points through various geometric criteria in a specific sequence to ensure that actual congruent points are most likely acquired. Similarly, the precision in the results can be associated to the identification of the optimal transformation from the acquired potential congruent points. As compared to the stimulated datasets, the real-life dataset demonstrated relatively low RMSE mainly due to the presence of noise and occlusion in the as-built model that may have resulted in slightly erroneous corner points, consequently, the transformation parameters computed from their congruent pairs were slightly less accurate.

Furthermore, it is also apparent that the computation time of dataset 3 is highly robust, however, dataset 2 witness relatively higher time. The underlying reason for time efficiency can be linked to the no. of extracted corner points from the models. The proposed methodology is highly efficient particularly with datasets having fewer extracted corner points, but the computation time is increasing exponentially in opposite cases. Hence, it can be assumed that the proposed method will take much higher time if the large building models with higher corner points are proposed. The combinatorial complexity in the processing can be improved using the RANSAC or other suitable optimization solutions to increase the time efficiency of the proposed method.

Datasets	No. of extracted corner points	Processing time (s)	RMSE (mm)
1	16	3.27	0.47
2	22	7.55	1.09
3	08	1.36	7.59

Table 1. Registration details of datasets.

5. CONCLUSION

The paper is a part of ongoing research that addresses the congruency problem in coarse registration and introduces a novel method that employs the corner points of building structure and finds their congruent pairs to compute the optimum transformation. Experimentation performed on building datasets (including real-life) with different geometries demonstrate its success in the Scan-vs-BIM problem. The result indicated the accurate registration of models, however, it is also found that the computation time is dependent on the corner points extracted from models, hence the proposed method can be computationally expensive for large datasets. In the future, it is planned to improve the method for its practical utilization in large datasets.

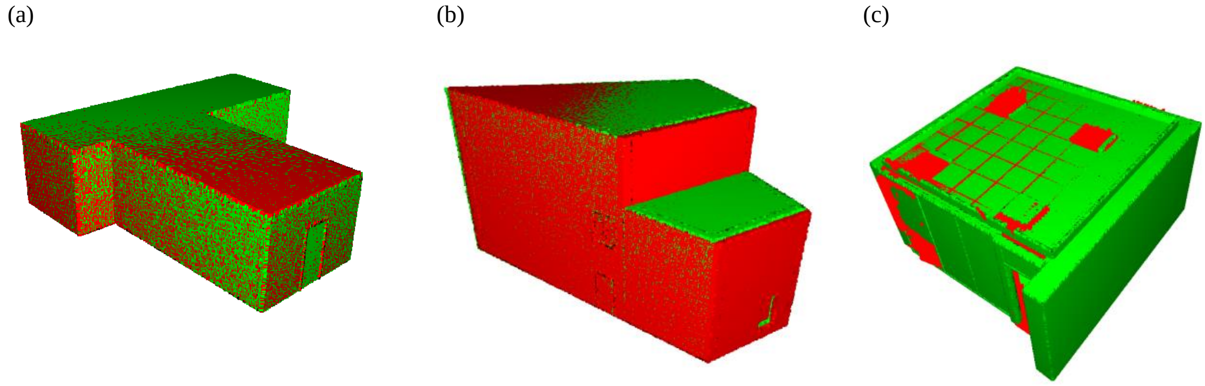

Figure 6. Visualization of registered models from (a) dataset 1 (b) dataset 2, and (c) dataset 3

REFERENCES

1. Tuttas, S.; Braun, A.; Borrmann, A.; Stilla, U. Acquisition and consecutive registration of photogrammetric point clouds for construction progress monitoring using a 4D BIM. *PFG–journal of photogrammetry, remote sensing and geoinformation science* **2017**, *85*, 3-15.
2. Omar, H.; Dulaimi, M. Using BIM to automate construction site activities. *Building Information Modelling (BIM) in Design, Construction and Operations* **2015**, *149*, 45.
3. Golparvar-Fard, M.; Savarese, S.; Peña-Mora, F. Interactive Visual Construction Progress Monitoring with D4 AR—4D Augmented Reality—Models. In Proceedings of Construction Research Congress 2009: Building a Sustainable Future; pp. 41-50.
4. Rebolj, D.; Pučko, Z.; Babič, N.Č.; Bizjak, M.; Mongus, D. Point cloud quality requirements for Scan-vs-BIM based automated construction progress monitoring. *Automation in Construction* **2017**, *84*, 323-334.
5. Golparvar-Fard, M.; Pena-Mora, F.; Savarese, S. Automated progress monitoring using unordered daily construction photographs and IFC-based building information models. *Journal of Computing in Civil Engineering* **2014**, *29*, 04014025.
6. Bueno, M.; Bosché, F.; González-Jorge, H.; Martínez-Sánchez, J.; Arias, P. 4-Plane congruent sets for automatic registration of as-is 3D point clouds with 3D BIM models. *Automation in Construction* **2018**, *89*, 120-134.
7. Pavan, N.L.; dos Santos, D.R.; Khoshelham, K. Global Registration of Terrestrial Laser Scanner Point Clouds Using Plane-to-Plane Correspondences. *Remote Sensing* **2020**, *12*, 1127.
8. Zong, W.; Li, M.; Zhou, Y.; Wang, L.; Xiang, F.; Li, G. A Fast and Accurate Planar-Feature-Based Global Scan Registration Method. *IEEE Sensors Journal* **2019**, *19*, 12333-12345.
9. Dong, Z.; Liang, F.; Yang, B.; Xu, Y.; Zang, Y.; Li, J.; Wang, Y.; Dai, W.; Fan, H.; Hyyppä, J. Registration of large-scale terrestrial laser scanner point clouds: A review and benchmark. *ISPRS Journal of Photogrammetry and Remote Sensing* **2020**, *163*, 327-342.
10. Besl, P.J.; McKay, N.D. Method for registration of 3-D shapes. In Proceedings of Sensor fusion IV: control paradigms and data structures; pp. 586-606.
11. Yang, J.; Li, H.; Jia, Y. Go-icp: Solving 3d registration efficiently and globally optimally. In Proceedings of Proceedings of the IEEE International Conference on Computer Vision; pp. 1457-1464.
12. Pavlov, A.L.; Ovchinnikov, G.W.; Derbyshev, D.Y.; Tsetserukou, D.; Oseledets, I.V. AA-ICP: Iterative closest point with Anderson acceleration. In Proceedings of 2018 IEEE International Conference on Robotics and Automation (ICRA); pp. 3407-3412.
13. Tazir, M.L.; Gokhool, T.; Checchin, P.; Malaterre, L.; Trassoudaine, L. CICP: Cluster Iterative Closest Point for sparse–dense point cloud registration. *Robotics and Autonomous Systems* **2018**, *108*, 66-86.
14. Xu, Y.; Boerner, R.; Yao, W.; Hoegner, L.; Stilla, U. Pairwise coarse registration of point clouds in urban scenes using voxel-based 4-planes congruent sets. *ISPRS journal of photogrammetry and remote sensing* **2019**, *151*, 106-123.
15. Rusu, R.B.; Blodow, N.; Beetz, M. Fast point feature histograms (FPFH) for 3D registration. In Proceedings of 2009 IEEE international conference on robotics and automation; pp. 3212-3217.
16. Stamos, I.; Leordeanu, M. Automated feature-based range registration of urban scenes of large scale. In Proceedings of 2003 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2003. Proceedings.; pp. II-Ii.
17. Xiao, J.; Adler, B.; Zhang, J.; Zhang, H. Planar segment based three-dimensional point cloud registration in outdoor environments. *Journal of Field Robotics* **2013**, *30*, 552-582.
18. Ge, X.; Wunderlich, T. Surface-based matching of 3D point clouds with variable coordinates in source and target system. *ISPRS Journal of Photogrammetry and Remote Sensing* **2016**, *111*, 1-12.
19. Yang, B.; Zang, Y. Automated registration of dense terrestrial laser-scanning point clouds using curves. *ISPRS journal of photogrammetry and remote sensing* **2014**, *95*, 109-121.
20. Yang, B.; Dong, Z.; Liang, F.; Liu, Y. Automatic registration of large-scale urban scene point clouds based on semantic feature points. *ISPRS Journal of Photogrammetry and Remote Sensing* **2016**, *113*, 43-58.
21. Bolles, R.C.; Fischler, M.A. A RANSAC-based approach to model fitting and its application to finding

cylinders in range data. In Proceedings of IJCAI; pp. 637-643.
22. Tombari, F.; Salti, S.; Di Stefano, L. Unique signatures of histograms for local surface description. In Proceedings of European conference on computer vision; pp. 356-369.
23. Glent Buch, A.; Yang, Y.; Kruger, N.; Gordon Petersen, H. In search of inliers: 3d correspondence by local and global voting. In Proceedings of Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; pp. 2067-2074.
24. Cai, Z.; Chin, T.-J.; Bustos, A.P.; Schindler, K. Practical optimal registration of terrestrial LiDAR scan pairs. *ISPRS journal of photogrammetry and remote sensing* **2019**, *147*, 118-131.
25. Böhm, J.; Becker, S. Automatic marker-free registration of terrestrial laser scans using reflectance. In Proceedings of Proceedings of the 8th conference on optical 3D measurement techniques, Zurich, Switzerland; pp. 9-12.
26. Weinmann, M.; Weinmann, M.; Hinz, S.; Jutzi, B. Fast and automatic image-based registration of TLS data. *ISPRS Journal of Photogrammetry and Remote Sensing* **2011**, *66*, S62-S70.
27. Theiler, P.; Schindler, K. Automatic registration of terrestrial laser scanner point clouds using natural planar surfaces. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences* **2012**, *3*, 173-178.
28. Weber, T.; Hänsch, R.; Hellwich, O. Automatic registration of unordered point clouds acquired by Kinect sensors using an overlap heuristic. *ISPRS Journal of Photogrammetry and Remote Sensing* **2015**, *102*, 96-109.
29. Knopp, J.; Prasad, M.; Willems, G.; Timofte, R.; Van Gool, L. Hough transform and 3D SURF for robust three dimensional classification. In Proceedings of European Conference on Computer Vision; pp. 589-602.
30. Ge, X. Automatic markerless registration of point clouds with semantic-keypoint-based 4-points congruent sets. *ISPRS Journal of Photogrammetry and Remote Sensing* **2017**, *130*, 344-357.
31. Xu, Y.; Boerner, R.; Yao, W.; Hoegner, L.; Stilla, U. AUTOMATED COARSE REGISTRATION OF POINT CLOUDS IN 3D URBAN SCENES USING VOXEL BASED PLANE CONSTRAINT. *ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences* **2017**, *4*.
32. Al-Durgham, M.; Habib, A. A framework for the registration and segmentation of heterogeneous LiDAR data. *Photogrammetric Engineering & Remote Sensing* **2013**, *79*, 135-145.
33. Habib, A.; Ghanma, M.; Morgan, M.; Al-Ruzouq, R. Photogrammetric and LiDAR data registration using linear features. *Photogrammetric Engineering & Remote Sensing* **2005**, *71*, 699-707.
34. Cheng, X.; Cheng, X.; Li, Q.; Ma, L. Automatic registration of terrestrial and airborne point clouds using building outline features. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **2018**, *11*, 628-638.
35. Dold, C.; Brenner, C. Registration of terrestrial laser scanning data using planar patches and image data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences-ISPRS Archives 36 (2006)* **2006**, *36*, 78-83.
36. Von Hansen, W. Robust automatic marker-free registration of terrestrial scan data. *Proc. Photogramm. Comput. Vis* **2006**, *36*, 105-110.
37. Khoshelham, K. Automated localization of a laser scanner in indoor environments using planar objects. In Proceedings of 2010 International Conference on Indoor Positioning and Indoor Navigation; pp. 1-7.
38. Li, M.; Gao, X.; Wang, L.; Li, G. Automatic registration of laser-scanned point clouds based on planar features. In Proceedings of 2nd ISPRS International Conference on Computer Vision in Remote Sensing (CVRS 2015); p. 990103.
39. Li, L.; Yang, F.; Zhu, H.; Li, D.; Li, Y.; Tang, L. An improved RANSAC for 3D point cloud plane segmentation based on normal distribution transformation cells. *Remote Sensing* **2017**, *9*, 433.
40. Schnabel, R.; Wahl, R.; Klein, R. Efficient RANSAC for point-cloud shape detection. In Proceedings of Computer graphics forum; pp. 214-226.
41. Nurunnabi, A.; Belton, D.; West, G. Robust segmentation in laser scanning 3D point cloud data. In Proceedings of 2012 International Conference on Digital Image Computing Techniques and Applications (DICTA); pp. 1-8.
42. Poppinga, J.; Vaskevicius, N.; Birk, A.; Pathak, K. Fast plane detection and polygonalization in noisy 3D range images. In Proceedings of 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems; pp. 3378-3383.
43. Grant, W.S.; Voorhies, R.C.; Itti, L. Finding planes in LiDAR point clouds for real-time registration. In Proceedings of 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems; pp. 4347-4354.
44. Brenner, C.; Dold, C.; Ripperda, N. Coarse orientation of terrestrial laser scans in urban environments. *ISPRS journal of photogrammetry and remote sensing* **2008**, *63*, 4-18.
45. Kim, P.; Chen, J.; Cho, Y.K. Automated point cloud registration using visual and planar features for construction environments. *Journal of Computing in Civil Engineering* **2018**, *32*, 04017076.
46. Kim, C.; Son, H.; Kim, C. Fully automated registration of 3D data to a 3D CAD model for project progress monitoring. *Automation in Construction* **2013**, *35*, 587-594.
47. Liu, Y.-S.; Ramani, K. Robust principal axes determination for point-based shapes using least median of squares. *Computer-Aided Design* **2009**, *41*, 293-305.