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AUTOMATED GEOMETRIC-SEMANTIC DIGITAL TWINNING OF STAIRCASES FROM DENSE LASER SCANNER POINT CLOUDS BY PARAMETRIC PROTOTYPE MODELS

Mansour Mehranfar[1], Alexander Braun[1], and André Borrmann[1]
[1]Technical University of Munich, Munich, Germany

Abstract

Digital Twins (DTs) have become as valuable tools for management, and operation of assets. A main challenge, however, persists in the automated creation of high-quality buildings DTs, providing both precise geometry and semantics. This paper introduces a novel hybrid bottom-up, top-down approach for the automated creation of DT models of staircase structures using laser scanner point cloud. The proposed workflow involves separating inclined staircase points, designing parametric DT models, and model fitting through an optimization process. The results demonstrate the effectiveness of the proposed with an average accuracy of about 4 cm in determining the dimensions of the model's elements.

Introduction

The automatic creation of DTs for the built environment has emerged as a prominent and demanding field within the AEC domain (Volk et al., 2014; Bosché et al., 2015; Drobnyi et al., 2023). A DT is a virtual replica of physical assets that facilitates real-time simulation and monitoring. DTs offer numerous possibilities for resource and facility management, enabling more intelligent analysis and interactions (Drobnyi et al., 2023). When it comes to creating DT models for exiting buildings with rich semantic content and coherent geometry, an important first step is to acquire relevant data, especially visual and spatial data. In this regard, laser scanning technology plays a crucial role, enabling the meticulous collection of point cloud data and the creation of virtual replicas for both indoor and outdoor environments (Noichl and Borrmann, 2022; Pan et al., 2023; Abdollahi et al., 2023; Martens and Blankenbach, 2023). This technology plays a pivotal role in advancing the domains of building performance and sustainability.

In the past decade, significant progress has been achieved in the field of point cloud processing techniques and 3D scene understanding methodologies, with a specific emphasis on automatically generating accurate geometric-semantic DT models from point cloud data. Nevertheless, developing a comprehensive and precise algorithm for this purpose has encountered numerous challenges, primarily arising from noise, clutter, obstructions, and the representation of volumetric-semantic models (Ochmann et al., 2016). Furthermore, most of the existing approaches have primarily focused on creating 3D models of structural elements such as ceilings, floors, and walls while neglecting the intricate modeling of other structural components, notably staircases, which play a pivotal role in the reconstruction of DTs for multi-story buildings (Nikoohemat et al., 2020). This oversight can be attributed to the inherent complexities associated with indoor scenes and the intricacies involved in reconstructing staircase structures (Schmittwilken et al., 2009). Staircase structures assume diverse shapes and configurations based on varying specifications, making the automatic reconstruction of 3D models a challenging task.

In the realm of urban planning and facility management, digital staircase models are vital for optimizing pedestrian flow and enhancing public safety. In this regard, the automatic creation of digital staircase models from point cloud data empowers facility managers and builders to conduct virtual walkthroughs, identify potential conflicts, and reduce construction and maintenance costs.

In the research presented in this paper, the primary objective is to introduce an automated workflow that combines both bottom-up and top-down approaches to extract staircase points within the indoor environment and generate parametric DT models with coherent geometry. The key contribution lies in utilizing domain knowledge to formulate parametric models for the building's staircase structures and subsequently fitting the designed rough models to point cloud data to achieve a close representation of reality.

Background and related work

Digital building twin creation

With the increase in demands for the creation of DT models for the built environment, indoor digital twinning has become an intensively researched topic in AEC domain (Borrmann et al., 2023). In this context, laser scanners and photogrammetry technologies are the most modern and efficient measurement tools, facilitating the acquisition of accurate geometric and semantic information, which are widely used in the realm of automatic creation of 3D digital models. However, despite all progress made, the automatic creation of digital building twin from point cloud data remains only partially resolved, and most developed methods are designed for specific types of buildings and restricted to reconstructing specific kinds of objects based on use cases.

In this regard, Xiong et al. (2013) proposed an automated 3D reconstruction framework utilizing a voxelized point cloud to identify patches, such as walls, ceilings, and floors, by adhering to boundary constraints. Monszpart et al. (2015) proposed the regular arrangements of planes (RAP) technique for reconstructing indoor 3D scenes using point cloud data. The proposed method uses local plane-based approximations and global inter-plane relations to simplify the arrangement of planes fitted to the points of the environment. Ochmann et al. (2019) proposed an innovative approach for reconstructing volumetric building DT models, encompassing floor, ceiling, and wall elements. They employed a linear optimization framework to disjoint distinct 3D spaces and determine the positions of common wall instances shared among them. Tran and Khoshelham (2020) employed a reversible jump Markov Chain Monte Carlo (rjMCMC) algorithm to facilitate the application of shape grammar rules in the procedural-based reconstruction of 3D indoor models from dense point cloud data. Abdollahi et al. (2023) introduced a progressive model-driven approach for the 3D modeling of indoor spaces employing watertight predefined models. This approach initially segmented spaces into rectangular and non-rectangular regions with an even number of sides. Subsequently, a point density occupancy map is used to enhance the level of detail in the intrusion and protrusion parts of Manhattan and non-Manhattan models.

Recent advancements in artificial intelligence (AI) and machine learning (ML) technology provide an effective solution for accurate point cloud processing, reducing the manual effort required in creating DTs. In this regard, Mehranfar et al. (2022) proposed a hybrid bottom-up, top-down method using AI semantic segmentation network to separate the 3D space in simple and complex indoor point cloud. Mehranfar et al. (2023) also combined domain knowledge in construction and architectural design with the capabilities of AI techniques in scene understanding to create highly parameterized building models with rich semantic and coherent geometry from dense point clouds. The proposed method employs the parametric modeling approach and model fitting through an optimization process to overcome common indoor point cloud challenges, including noise, gap, and clutter. Kellner et al. (2023) developed a multi-step data-driven algorithm enriched with AI techniques for the 3D reconstruction of building models at Level of Development (LoD) 400. The proposed approach utilizes an AI semantic segmentation network to separate the following classes: doors, door leaves, windows, walls, ceilings, floors, and clutter. Subsequently, a 2D projection combined with a neighborhood graph structure is employed to partition 3D space within indoor environments, followed by applying the RANSAC plane fitting algorithm to reconstruct 3D models of walls. Ultimately, a bounding box is fitted to the points pertaining to each individual instance of door and window elements.

Staircase points detection and modeling

Staircase detection within point clouds and the subsequent creation of staircase DT models is an area of research that has received less attention compared to other applications of point cloud processing. Staircases exhibit diverse shapes and dimensions, and their visual representation can be influenced by different factors, such as structural design and the quality of the point cloud data. This complexity introduces challenges in developing robust and broadly applicable staircase detection algorithms. Additionally, utilizing ML approaches for staircase detection heavily relies on huge labeled datasets for network training purposes. The scarcity of such datasets specifically for staircases has impeded progress in research within this domain. Among the little research conducted on staircase point detection and digital model reconstruction, Schmittwilken et al. (2009) introduced a low-level module based on the random sample consensus (RANSAC) algorithm to generate planar polygonal patches for building facades and the surrounding ground. They employed Conditional Random Fields (CRFs) to classify patches into facade, window, door, and staircase classes, considering local neighborhood information and incorporating attribute grammar, including object partonomy and observable geometric constraints.

In 2009, Schmittwilken and Plümer (2009) proposed a top-down approach for reconstructing symmetric and partly recursive objects, such as a triple-run staircase from point cloud data. The proposed method utilizes an attribute grammar formulation using geometric dependencies for the design of 3D models and subsequently employs the random sample consensus paradigm for model selection and extraction of the geometric parameter of each 3D object. Sinha et al. (2014) presented a data-driven approach that employs a minimal 3D map representation and calculates step-like local features using point neighborhoods to detect staircase points. Yang et al. (2019) employed a bottom-up hierarchical semantic classification method, incorporating various semantic definitions, such as planarity of wall, ceiling, and floor surfaces at the geometric primitive level, to establish relationships between the staircase connection space and indoor space. For the coarse segmentation of staircase points, the height histogram of points is used to identify the void region between the planar surfaces of solid slabs and the connection space with staircases. Subsequently, the connected component algorithm is applied to cluster distinct pieces, planes, and clusters of staircases. Finally, the α-shapes algorithm is employed to construct the surface model for each step of the staircase.

In conclusion, the automatic creation of digital building twins using point cloud data is a research field constantly facing challenges such as complex space layouts, clutter, obstructions, and the need to provide methods for representing volumetric semantic models. The challenges become even more complex for elements such as staircases, which can have varying appearances based on their design. In the research presented in this paper, we aim to develop a hybrid bottom-up, top-down method for the automatic creation of a DT model for staircase structures using point cloud data. The proposed method leverages domain knowledge in construction and design to create para-

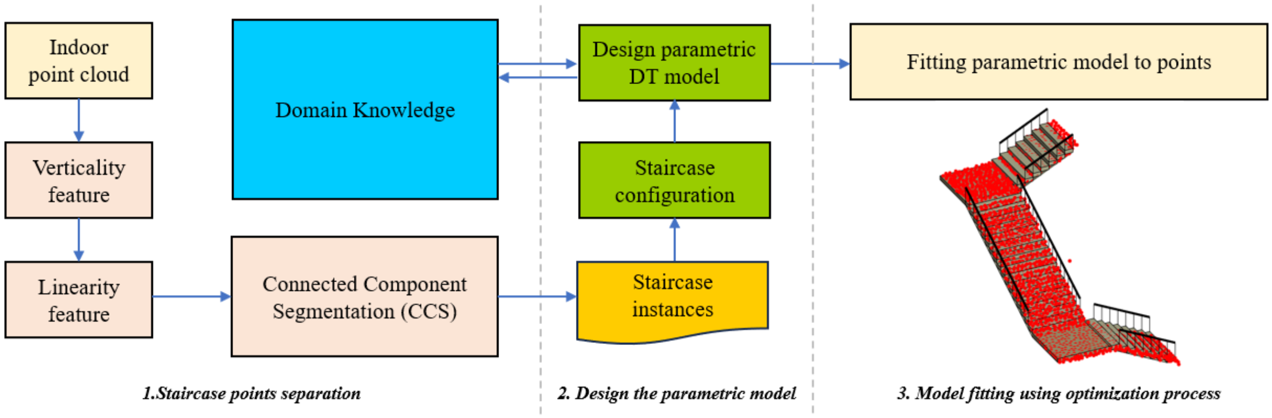


Figure 1: The proposed workflow for creating the DT model of the staircase.

metric models that can consider semantic relationships between components, allowing to overcome challenges such as noise and obstructions.

Methodology

As shown in Figure 1, the proposed workflow for the automatic creation of the DT model for staircase elements consists of three major steps, including 1) staircase points separation, 2) designing the parametric model of the staircase, and 3) model fitting using an optimization process. The details of the steps are given in the following subsections.

Staircase points separation

Staircase structures are typically inclined and constructed with a specific slope. Various factors, such as building regulations, architectural preferences, and the intended purpose of the staircases determine the inclination angle of a staircase. In residential and educational buildings, staircases are often designed with a relatively gentle incline to provide comfort and ease of use, such as for the convenience of (elderly) occupants. In the proposed method, the Verticality geometric feature is employed to distinguish inclined staircase points from other structural elements within the point cloud space, including vertically oriented walls and horizontally oriented ceilings and floors (Figure 2b).

To calculate the Verticality feature for each point in the point cloud space, the equation 1 is used with a neighborhood of 25 cm (Grilli et al., 2019). The selected neighborhood radius value ensure the presence of a minimum number of neighboring points for accurate estimation of Verticality features for the main structural elements, as well as small furniture objects.

$$Verticality = 1 - nz, \tag{1}$$

where nz is the normal vector value toward the Z axis, which is calculated by the covariance matrix and eigenvector values of the nearest neighboring points using equation 2 (Grilli et al., 2019):

$$c = \frac{1}{k}\sum_{i=1}^{n}(pi - \bar{p}).(pi - \bar{p})^T, \tag{2}$$

where k is the number of neighboring points, pi and p also refer to the 3D coordinates of the points being considered. Additionally, the eigenvalues and eigenvectors are determined by equation 3 where λ and $\vec{v}$ are eigenvalues and eigenvectors respectively (Grilli et al., 2019):

$$c.\vec{v}_j = \lambda_j.\vec{v}_j, \quad j \in \{0,1,2\} \tag{3}$$

Points associated with entirely horizontal elements are assigned a Verticality value of zero, while points pertaining to completely vertical elements are assigned a Verticality value of one. In this case, a confidence interval of 45%, characterized by approximate slopes ranging from 0.05% to 0.5%, is considered to extract the inclined points (Figure 2c).

The output of this process includes inclined staircase points, edge points of walls and ceilings, floor elements, noise points, and clutter. To extract points specific to each staircase instances, we adopt a two-step approach. Initially, the Linearity feature of the points is leveraged using equation 4 to eliminate the edge points of wall and ceiling elements (Figure 2e). Subsequently, the Connected Component Segmentation (CCS) algorithm is employed to segment points into distinct groups based on their connectivity, effectively isolating small segments that often appear as clutter within the point cloud space (Figure 2f) Trevor et al. (2013).

$$Linearity = \frac{\lambda_1 - \lambda_2}{\lambda_1} \tag{4}$$

As shown in Figure 3a, the extracted staircase lacks points corresponding to the horizontal planes of the staircase landing tread. This omission is due to the exclusion of horizontal points in the filtering process of the previous step. However, this information gap proves advantageous in subsequent steps for separating staircase components and their configuration analysis.

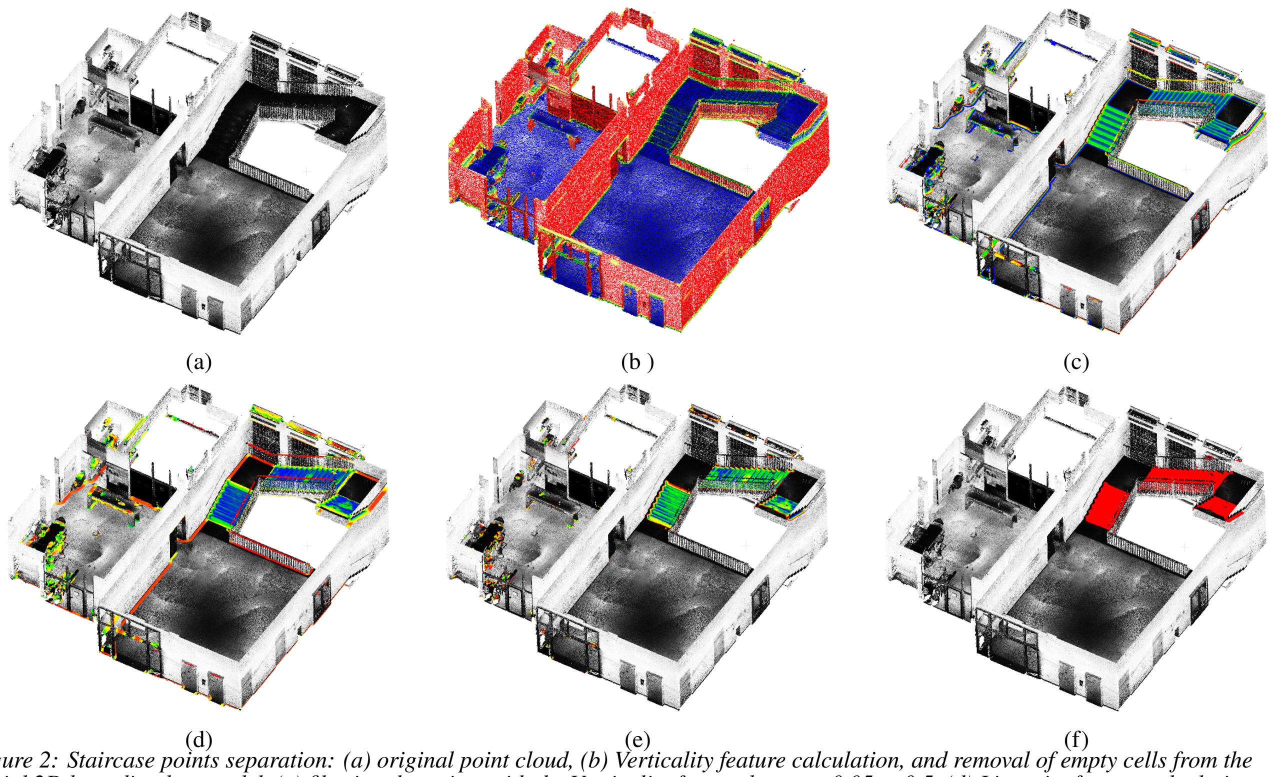


Figure 2: Staircase points separation: (a) original point cloud, (b) Verticality feature calculation, and removal of empty cells from the initial 2D bounding box model, (c) filtering the points with the Verticality feature between 0.05 to 0.5, (d) Linearity feature calculation to filter noise and unwanted furniture points, (e) staircase points after noise removal, (f) applying the CCS method to segment staircase points.

Design the parametric model of staircase

The structural configuration of interconnecting staircases between building levels frequently comprises multiple stair tread parts and incorporates two or more landing treads. The design and structural morphology of these staircases is inherently influenced by factors such as the flow of ingress and egress and the placement of landing treads. To quantify the number of landings and determine their direction, the central portion of the staircase points is examined using 3D point density analysis (Figure 3b). This analysis reveals that the extracted staircase element comprises three flows and two landing treads that run from left to right, top to down, and right to left, respectively (Figure 3c). This information serves as valuable input for subsequent steps, particularly within the parametric design of the staircase structure.

The staircase structure typically consists of distinct primary components such as step riser, step tread, railing etc. The differences between staircases primarily pertain to the number and dimensions of the primary components (e.g. number of steps, width, length, depth of steps, and landing treads) as well as the specific modes of flow rotation and positioning of the landing tread. Specifically, we consider four possible rotation types, denoted by numerical identifiers 1, 2, 3, and 4, corresponding to left-to-right, right-to-left, bottom-to-top, and top-to-bottom orientations, respectively (Figure 4a). For instance, the primary configuration of the extracted staircase is represented by the array "142" (Figure 4b). This signifies that the staircase in question consists of three flows and two landing treads, each being successively positioned from left to right, top to bottom, and right to left. Consequently, a library of parametric models is systematically generated based on the number of landing treads and flow patterns.

Model fitting using optimization process

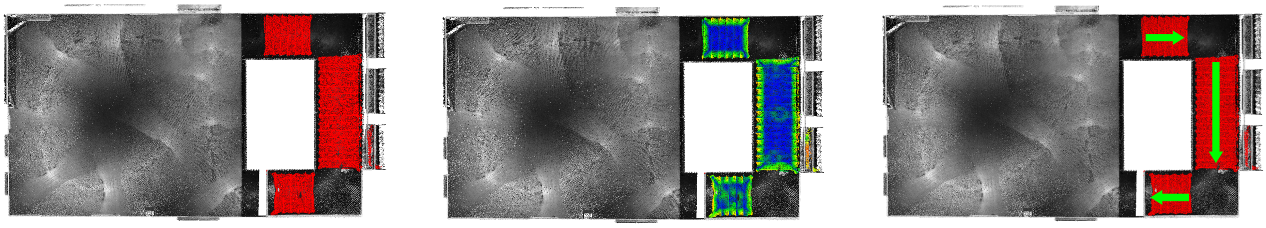
The designed parametric model has low geometric accuracy but a consistent semantic topology. To determine the optimal geometric values of the DT model's components, the optimization process is used to fit the designed parametric model to the extracted staircase points. The Nelder-Mead optimization algorithm fits the initial parametric model to points (Nelder and Mead, 1965). Within this context, the objective function employed during the model-to-point fitting process is defined as follows (5) :

$$Obj = min(G + \frac{F}{10}) \tag{5}$$

The term G refers to the distance between the points and the step planes, which is a critical factor for the vertical alignment of the parametric model toward the staircase points (6) (Figure 5):

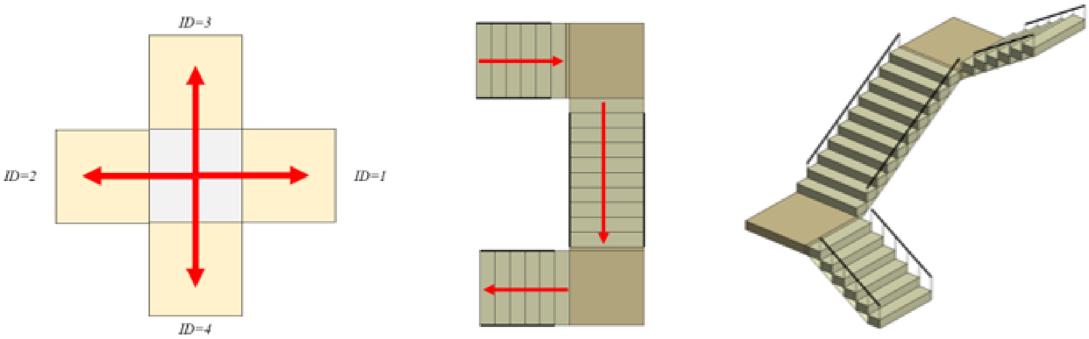
$$G = \sum_{i=1,j=1}^{n,k} |p_i - plane_j| \tag{6}$$

where the p_i is the staircase point i, $plane_j$ is the jth plane of parametric model, p_{stairs} is the number staircase points



(a) (b) (c)

Figure 3: Staircase configuration: (a) staircase points, (b) central part of staircase, (c) separated flows and their orientation.



(a) (b) (c)

Figure 4: Determining the type of staircase based on the number of flows and the number of landing treads: (a) possible rotation directions, (b) design the configuration of the parametric model for the staircase instance with two landing treads and flow's ID array [1 4 2], (c) highly parameterized DT model of the staircase.

and p_{in} is the number staircase points inside the step box of staircase model.

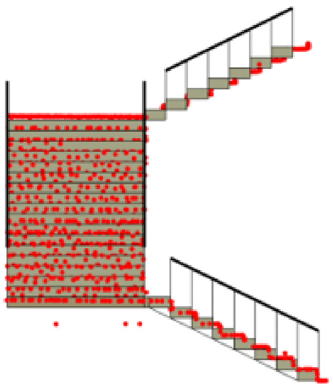


Figure 5: Fitting parametric model of staircase to points; Vertical alignment of the parametric model toward the staircase points (term G).

The term F is related to the number of steps present within each flow connecting the landing treads, as well as the placement of the parametric model planes on the staircase points on the X-Y plane (7) (Figure 6):

$$F = |p_{stairs} - \sum_{i=1}^{steps} p_{in}| \qquad (7)$$

where the p_{stairs} is the number of staircase points and p_{in} is the number of staircase points inside the step box of the staircase model. To enhance the process of fitting a model to the points, in each iteration, the 3D points inside each box of the model are extracted and used in the optimization process. This includes the points on the landing treads that were omited during the staircase points separation step.

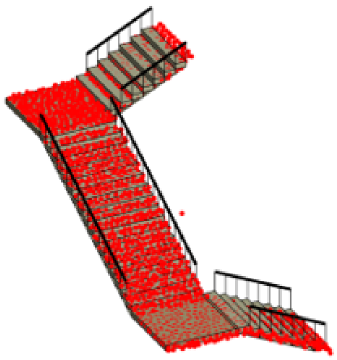


Figure 6: Fitting parametric model of staircase to points; placement of the parametric model planes on the staircase points (term F).

During the model fitting process, the points inside each box of the DT models are extracted and appended to the previously extracted staircase points to improve the model fitting, specifically in the parts of landing treads. In between, adding excessive steps may not change the overall distance value between the staircase points and the model planes. To address this challenge, a penalty factor is incorporated into the objective function. Specifically, if an additional step does not encompass any points within the 2D X-Y plane, a penalty value of 10000 is appended to the final value of the objective function (8):

$$if\, p_{in} == 0 \;\; then \;\; Obj = min(G + \frac{F}{10}) + 10000 \qquad (8)$$

Result

To evaluate the proposed method, the dense point cloud dataset is used that has been captured by the authors at the City campus of the Technical University of Munich (TUM). The TUM building in question (Building 1) is a multi-story structure comprising four floors. The point cloud data was captured using NavVis laser scanner with a spatial resolution of 0.1 cm (https://www.navvis.com/). Figure 7 illustrates an overview of the data.

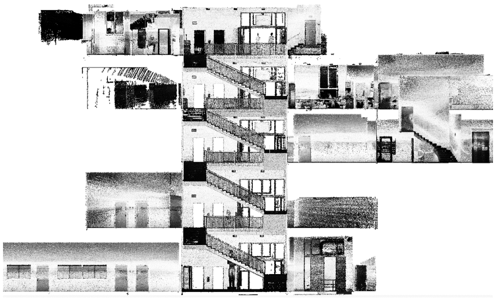


Figure 7: Overview of the TUM Building 1 data.

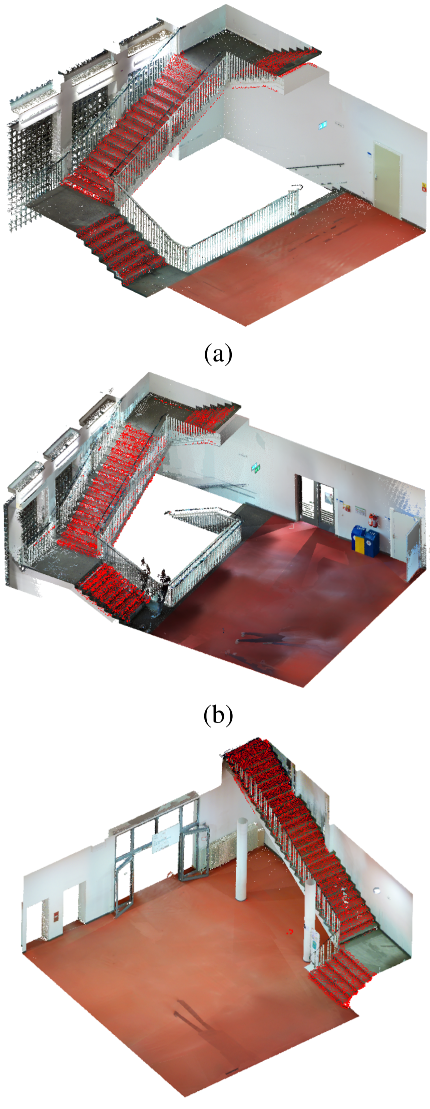
Experimental results on staircase points separation

To extract the staircase points within each floor's point cloud, first, the Verticality feature is calculated for the points in each floor by considering the neighborhood radius of 0.25 cm. Next, the inclined points of staircases are extracted from the point cloud space considering a confidence interval of 45%, which encompasses the points with the Verticality feature between 0.05 to 0.5. As mentioned in Section 2, the result of this step contains noise and clutter. In this regard, the linearity feature is calculated for each point considering the neighborhood radius of 0.50 cm to detect the noise and boundary points between the ceiling, floor, and wall elements. Finally, the CCS method is employed to segment the points belonging to each staircase instance. In this case, the distance threshold for connecting the points in each segment is considered as 25 cm and the minimum number of points to segment each staircase instance is specified equal to 5000. Figure 8 shows the result of staircase point separation for different floors of the TUM Building 1 dataset.

To assess the effectiveness of the staircase points separation step, the manually annotated point cloud and the extracted staircase points are compared, and the results are reported in Table 3 based on Equations (9-11). In this regard, an overall accuracy of about 95% for separating staircase points from other elements in the point cloud space highlights the performance of the proposed workflow for separating staircase points, which significantly influences the quality of the model fitting steps.

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

$$Recall = \frac{TP}{TP+FN} \tag{10}$$



(a)

(b)

(c)

Figure 8: The result of staircase points separation for the TUM Building 1 dataset: (a) floor-2, (b) floor-3, and (c) floor-4.

$$F\text{-}score = 2.\frac{Precision.Recall}{Precision+Recall} \tag{11}$$

Experimental results on creation parametric model of staircase

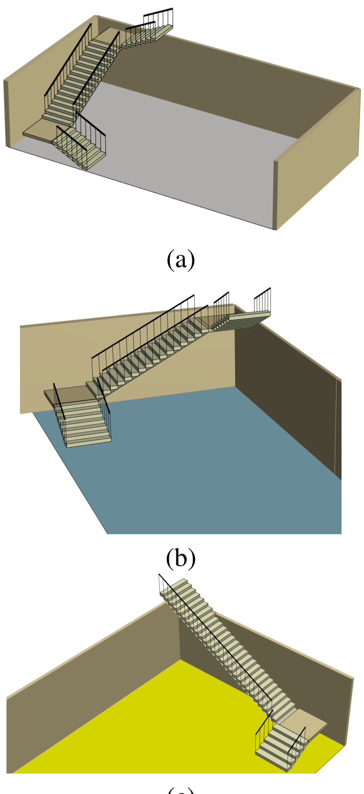
First, the central parts of the extracted staircase points are examined to design the parametric DT model for the extracted staircase instances. In this regard, the structure of staircase instances in the point cloud of the second to third floor is determined by array 142. This means the corresponding staircase structure consists of two landing treads and three flows formed from left to right, up to down, and right to left, respectively. Also, the staircase structure extracted in the point cloud floor fourth is determined by array 32, meaning that this staircase consists of one landing tread element and two flows, which are formed from bottom to top and from right to left.

Subsequently, parametric DT models are designed based

Table 1: Accuracy evaluation of staircase points separation.

Dataset	F (2)	F (3)	F (4)
Precision	0.75	0.60	0.70
Recall	0.80	0.73	0.85
F-Score	0.77	0.64	0.75
Overall accuracy = 0.95			

on the provided information for each staircase instance. These models incorporate various parameters and consider their relation, including the number of steps between landing treads and dimensional values of geometric properties such as width, depth, and height, which, in addition to maintaining the semantic relation between the staircase components, also promotes geometric integrity. Following this, the designed parametric models are fitted to the extracted staircase points to estimate optimal values for the parameters of the created DT models. As discussed earlier, the Nelder-Mead optimization method and the objective function are employed to fit the model to the points and extract optimal parameters for the designed DT models, ensuring that the models closely resemble real-world structures.



(a)

(b)

(c)

Figure 9: The result of staircase points separation for TUM Building 1 dataset: (a) floor-2, (b) floor-3, and (c) floor-4.

To evaluate the proposed method for the automatic creation of the staircase DT model, the differences between distances and dimensional values of the staircase components in the reference DT models and the generated models are calculated. For each dataset, the standard metric of mean error is presented in Table 4. Furthermore, the distance between the model and the extracted staircase points is measured for each dataset, indicating the closeness of the created model to the captured point cloud. The overall mean accuracy of about 0.04 m highlights the performance and effectiveness of the proposed method for the automatic creation of DT models for staircase structures in the built environment.

Table 2: Accuracy evaluation of staircase DT creation.

Dataset	F (2)	F (3)	F (4)
Flights:			
Width	0.04	0.05	0.04
Depth	0.03	0.04	0.04
Height	0.02	0.03	0.03
Number of Steps	100%	97%	93%
Landing treads:			
Width	0.04	0.05	0.04
Depth	0.03	0.04	0.05
Height	0.02	0.03	0.04
Overall accuracy	0.03	0.04	0.04
Points to Model	0.08	0.11	0.07

Conclusion

This research presents a novel hybrid bottom-up, top-down method to create the highly parameterized DT model of a staircase structure. The proposed method aligns existing knowledge in the design and construction of building elements with the parametric modeling framework, allowing us to consider different degrees of freedom to model a wide range of staircase models in the real world. By considering semantic relationships between staircase components, the presented approach provides solutions to overcome challenges such as point cloud obstruction, noise, and complexity in the representation of 3D geometric models. In this regard, an overall mean error of about 0.04 m in creating a highly parameterized DT model for a staircase structure with different shapes and designs promises significant progress in the field of ”Scan-to-BIM” that ultimately provides high-quality DTs with rich semantics and coherent geometry. Despite diligent considerations, the proposed method has inherent limitations in creating digital models of round staircases with non-Manhattan designs, which will be addressed in future works.

Acknowledgments

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References

Abdollahi, A., Arefi, H., Malihi, S., and Maboudi, M. (2023). Progressive model-driven approach for 3d modeling of indoor spaces. Remote Sensing, 23(13).

Borrmann, A., Biswanath, M., Braun, A., Chen, Z., Cremers, D., Heeramaglore, M., Hoegner, L., Mehranfar, M., Kolbe, T., Petzold, F., Rueda, A., Solonets, S., and Zhu, X. (2023). Artificial intelligence for the automated creation of multi-scale digital twins of the built world – ai4twinning. In Proc. of the 18th 3D GeoInfo Conference.

Bosché, F., Ahmed, M., Turkan, Y., Haas, C., and Haas, R. (2015). Heritage building information modeling (h-bim) applied to a stone bridge. Automation in Construction, 49.

Drobnyi, V., Hu, Z., Fathy, Y., and Brilakis, I. (2023). Construction and maintenance of building geometric digital twins: State of the art review. Sensors, 23(9).

Grilli, E., Farella, E., Torresani, A., and Remondino, F. (2019). Geometric features analysis for the classification of cultural heritage point clouds. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-2/W15.

Kellner, M., Stahl, B., and Reiterer, A. (2023). Reconstructing geometrical models of indoor environments based on point clouds. Remote Sensing, 15(18).

Martens, J. and Blankenbach, J. (2023). Vox2bim + - a fast and robust approach for automated indoor point cloud segmentation and building model generation. PFG – Journal of Photogrammetry Remote Sensing and Geoinformation Sciencen, 91(4):273–294.

Mehranfar, M., Braun, A., and Borrmann, A. (2022). A hybrid top-down, bottom-up approach for 3d space parsing using dense rgb point clouds. In Proc. of European Conference on Product and Process Modeling.

Mehranfar, M., Braun, A., and Borrmann, A. (2023). Automatic creation of digital building twins with rich semantics from dense rgb point clouds through semantic segmentation and model fitting. In Proc. of the 30th Int. Conference on Intelligent Computing in Engineering (EG-ICE).

Monszpart, A., Mellado, N., Brostow, G., and Mitra, N. (2015). Rapter: rebuilding man-made scenes with regular arrangements of planes. ACM Transactions on Graphics, 34(4):1–12.

Nelder, J. and Mead, R. (1965). A simplex method for function minimizatio. International Journal of Mathematics and Computers in Simulation, 7:308–313.

Nikoohemat, S., Diakité, A., Zlatanova, S., and Vosselman, G. (2020). Indoor 3d reconstruction from point clouds for optimal routing in complex buildings to support disaster management. Automation in Construction, 13:103109.

Noichl, F. and Borrmann, A. (2022). Automated deterministic model-based indoor scan planning. In Proc. of European Conference on Product and Process Modeling.

Ochmann, S., Vock, R., and Klein, R. (2019). Automatic reconstruction of fully volumetric 3d building models from oriented point clouds. ISPRS Journal of Photogrammetry and Remote Sensing, 151:251–262.

Ochmann, S., Vock, R., Wessel, R., and Klein, R. (2016). Automatic reconstruction of parametric building models from indoor point clouds. Automation in Construction, 38:94–103.

Pan, Y., Braun, A., and Borrmann, Andre Brilakis, I. (2023). 3d deep-learning-enhanced void-growing approach in creating geometric digital twins of buildings. Smart Infrastructure and Construction, 176(1):24–40.

Schmittwilken, J. and Plümer, L. (2009). Model selection for composite objects with attribute grammars. In 12th AGILE International Conference on Geographic Information Science. Leibniz Universität Hannover, Germany.

Schmittwilken, J., Ying, M., FörstnerLutz, W., and Plümer, L. (2009). Construction and maintenance of building geometric digital twins: State of the art review. Annals of GIS, 15(2):117–126.

Sinha, A., Papadakis, P., and Elar, M. (2014). A staircase detection method for 3d point clouds. In 13th International Conference on Control Automation Robotics & Vision (ICARCV).

Tran, H. and Khoshelham, K. (2020). Procedural reconstruction of 3d indoor models from lidar data using reversible jump markov chain monte carlo. Remote Sensing, 12(5).

Trevor, A., Gedikli, S., Rusu, R., and Christensen, H. (2013). Efficient organized point cloud segmentation with connected component. In Proceedings of Semantic Perception Mapping and Exploration, pages 1–6.

Volk, R., Stengel, J., and Schultmann, F. (2014). Building information modeling (bim) for existing buildings — literature review and future needs. Automation in Construction, 38:109–127.

Xiong, X., Adan, A., Akinci, B., and Huber, D. (2013). Automatic creation of semantically rich 3d building models from laser scanner data. Automation in Construction, 31:325–337.

Yang, F., Liang, Y., Li, D., Su, F., Zhu, H., Zuo, X., and Li, L. (2019). Detection of space connectivity from point cloud for stair reconstruction. Environmental Science.