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AUTOMATED BOTTOM-UP, TOP-DOWN METHOD FOR CREATING DIGITAL STAIRCASE MODELS FROM DENSE POINT CLOUDS USING PARAMETRIC PROTOTYPE MODELS AND MODEL FITTING

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SUMMARY: *Digital building models have become a transformative tool in the management and monitoring of assets in the built world. Laser scanners are valuable tools for creating digital building models through Scan-to-BIM algorithms, capturing the as-built status of the environment in the form of point clouds. However, a main challenge persists in the automated creation of digital models from these point clouds, providing both coherent geometry, and semantics. Staircase elements are vital in multilevel buildings, facilitating essential vertical movement and serving as crucial emergency evacuation routes. This paper proposes a hybrid bottom-up, top-down approach for the automatic creation of digital staircase models using laser scanner point clouds. The workflow involves separating staircase points, designing parametric models, and model fitting through optimization. The proposed method is validated using eight real laser scanning point clouds containing highly diverse stair configurations. The results demonstrate the effectiveness of the proposed method in automatically creating high-quality digital staircase models with coherent geometry.*

KEYWORDS: *Digital model, Laser scanner, Scan-to-BIM, Point cloud, Bottom-up, Top-down approach, Model fitting.*

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1. INTRODUCTION

Digital building models have revolutionized the Architecture, Engineering, Construction, and Operations (AECO) domain by providing detailed representations of structures and improving precision and efficiency in management, planning, and maintenance (Duong and Lin, 2022; Elshabshiri et al., 2025). A semantic digital building model accurately represents structural components and integrates data to reflect the physical asset's evolving behaviors and performance characteristics. This enables advanced resource and facility management, allowing more intelligent analysis and decision making (Mahmoodian et al., 2022; Yoon, 2023). In built environments, staircase structures serve both utilitarian and architectural functions, facilitating vertical movement and contributing to spatial aesthetics. Creating as-built digital staircase models and accurate documentation of their dimensions and design streamline maintenance processes, enhance safety inspections, and facilitate renovations. The essential prerequisite for creating as-built digital staircase models with rich semantics and coherent geometry is to capture precise geometric data (Eyre et al., 2015). In this context, laser scanning technology, with the swift collection of point cloud data and the creation of virtual replicas for indoor and outdoor environments, is recognized as a valuable tool for developing methods for creating digital models (Chen et al., 2020).

Currently, creating high-quality digital models from point cloud data demands significant manual effort and time. Despite the significant progress made in the engineering and computer vision algorithms, the automatic creation of accurate geometric-semantic digital staircase models from point cloud data remained challenging. The indoor environment is inherently associated with challenges such as complex space layouts, clutter, and obstructions. This requires developing and utilizing advanced point cloud processing techniques and 3D scene understanding methodologies to interpret raw point cloud data and separate staircase points (Mehranfar et al., 2024). Moreover, the inherent complexity of staircase configurations and the intricacies involved in accurately capturing their spatial dimensions necessitate a comprehensive understanding of computational geometry principles and advanced algorithms to effectively process and interpret the point cloud data, estimate the geometric parameters, and create a consistent digital model.

1.1 Digital staircase modeling for built environment digitalization

Staircases are one of the critical elements in the built environment, facilitating vertical movement, connecting spaces, and ensuring accessibility across building floors. In this regard, the digitalization of staircases is essential for several reasons:

- Safety and Compliance: staircases must comply with safety standards and building codes. Digital models enable the evaluation of these structures for compliance with regulations, including accessibility standards.
- Replanning: digital staircase models provide documentation of existing conditions, enabling effective planning for maintenance or renovation projects.
- Integration in smart built environment digital model: as part of a larger digital model, staircases contribute to the overall analysis of built environment performance, including digital model integrity, user flow simulations, and emergency evacuation modeling.

Despite their structural and functional significance, staircases often pose significant challenges in the digitalization process due to their complex geometries and diverse designs. Traditional manual modeling from point clouds is labor-intensive and error-prone, especially for intricate geometries like spiral or irregular staircases. In the Scan-to-BIM domain, automated staircase digitalization plays a pivotal role. The automatic generation of digital staircase models from point clouds provides a robust solution, enabling seamless integration of these critical structures into Building Information Modeling (BIM) workflows. Automation enhances the accuracy and efficiency of built environment digitalization, offering:

- Time and cost savings: developing an automated method for creating digital staircase models using the laser scanner point cloud reduces the labor and expertise required for manual modeling.
- Standardization: using standard descriptors within the creation of the digital staircase models ensures interoperability with existing BIM systems and compliance with established BIM standards such as Industry Foundation Classes (IFC).

1.2 Contribution

In this paper, we propose a hybrid bottom-up, top-down method for the automated creation of digital staircase models from dense laser scanner point cloud data. The proposed method leverages domain knowledge in designing and constructing staircases within indoor environments to generate parametric digital models with coherent geometry. The main contribution lies in utilizing domain knowledge to extract inclined staircase points and formulate parametric staircase models with various configurations and designs, subsequently fitting the coarse models to point cloud data to accurately estimate the real parameter values. Using the parametric modeling approach, the proposed algorithm can create dynamic digital models, allowing manipulation by adjusting parameter values using predefined constraints. This capability provides a foundation for frequent geometric updates throughout the operational lifespan of a facility and for planning and management purposes. The main contributions of our research are the following:

- Automated hybrid bottom-up, top-down approach for staircase point separation and digital model reconstruction.
- Development of an end-to-end bottom-up framework for separating staircase points with rectangular and non-rectangular shape configurations.
- Utilization of domain engineering knowledge to create a library of parametric staircase models.
- Creation of digital staircase models through parametric model fitting.

The present paper is structured as follows: Section 2 presents a literature review of the methods developed for creating digital staircase models using point cloud data. Section 3 details the proposed methodology from a theoretical point of view. Section 4 provides several case studies to demonstrate the feasibility and effectiveness of the proposed approach. Finally, Section 5 examines the key findings and explores potential avenues for future research.

2. BACKGROUND

2.1 Creation of digital building models

Over the past decade, BIM and the creation of digital building models from point cloud data, a process known as Scan-to-BIM, have become highly sought after in the Architecture, Engineering, Construction, and Operations (AECO) industries (Turkan et al., 2024; Madubuike and Anumba, 2022). These digital models play a vital role in efficient building operations, providing comprehensive information that significantly aids in maintenance, repairs, and overall facility management (Austin et al., 2020; Borrmann et al., 2018; Choi et al., 2024).

Laser scanners and photogrammetry technologies are the most modern and efficient three-dimensional (3D) data capturing tools, enabling the acquisition of precise geometric and semantic information essential for creating digital building models. However, the raw building point clouds are generally complex and unstructured. This necessitates further processing steps and deriving higher-level contextual information to support scene understanding and automate the geometry provision tasks (Bassier and Vergauwen, 2020). In the realm of computer vision and computational modeling, extensive research has been conducted on the digitization of the built environment. Several authors have developed various methodologies to automatically process point cloud data and generate digital building models (Bosch´e et al., 2015). Within this context, most of the developed methods rely on data-driven, model-driven, and Artificial Intelligence (AI)-based approaches (Mehranfar et al., 2024).

In the data-driven methods, here denoted as bottom-up methods, the point cloud interpretation begins by labeling several random seed points. This process gradually extends to all points, systematically incorporating additional data points until a higher-level representation of the surface, volume, or model is achieved (Xiong et al., 2023; Kong et al.. 2023). These higher levels are commonly represented by meshes (Marton et al., 2009), voxels (Vo et al., 2015), and planes (Poux et al., 2022; Gao et al., 2024). Normal vectors, curvatures, and RGB values are typical features used in common data-driven methods, such as Region Growing (RG), Random Sample Consensus (RANSAC), model-based, and edge-based approaches, to differentiate between geometrical and spectral details of various surfaces (Nikoohemat et al., 2020). The data-driven approach ensures that the model is comprehensive and detailed, effectively capturing the intricacies of the building's structure. This results in digital building models that closely resemble the real world, providing a highly accurate representation. However, these approaches are particularly sensitive to data quality, especially with regard to occlusions. Their performance may decline when faced with challenges such as clutter or noise.

The model-driven approach, here also denoted as top-down methods, uses predefined geometry, relationships, and constraints in point cloud processing and digital building model creation to ensure the geometric coherence of the resulting model (Tran and Khoshelham, 2020; Adan et al., 2023). This approach begins by segmenting a point cloud into compositional sub-groups based on the similarities and dissimilarities of various elements. Using a top-down strategy, perceptions begin at the highest level of abstraction and move toward finer granularity. This systematic progression helps maintain a structured and coherent model throughout the reconstruction process (Ochmann et al., 2019). However, the major challenge of this approach lies in accurately defining the fundamental geometric relationships and constraints that are crucial to achieving optimal results.

In contrast to conventional bottom-up and top-down data-driven approaches, AI models can learn various characteristics of different datasets without the need for manual selection and fine-tuning of decisive features (Pan et al., 2023). The AI networks for point cloud processing utilize a set of training data to learn the rules for assigning meaningful labels to points (Maru et al., 2023). This task can be divided into semantic segmentation, classification, and instance segmentation. Semantic segmentation involves assigning a label to each point in the point cloud, classifying each point based on its context (Xue et al., 2019). Classification refers to identifying and labeling the entire point cloud or large sections of it as a whole (Park and Cho, 2021). Instance segmentation goes a step further by not only labeling points but also distinguishing between different instances of the same element class within the point cloud (Maximilian et al., 2023). However, separating and identifying building structural elements within the point cloud requires an extensive and diverse dataset to train the models effectively. This dataset must cover various building types, structures, and conditions to ensure the model's robustness and accuracy.

2.2 Staircase points separation and modeling

Despite significant advancements in automated methods for creating digital building models, research has primarily focused on main structural elements (e.g., wall, ceiling, floor, and column) and openings (door and window). In contrast, the detection of staircases within point clouds and their subsequent digital modeling has received less attention in the realms of computer vision and digital twinning. Staircases are designed with various configurations, shapes and sizes, ranging from straight flights to spiral and helical forms, each with unique geometrical characteristics. This variability is compounded by architectural details such as handrails, balustrades, and landings, which add further complexity. These factors make the process of detecting staircase points challenging and hinder the development of a generalized method for creating staircase geometry models.

In the limited body of conducted research, Schmittwilken et al. proposed a low-level module based on the RANSAC (Random sample consensus) algorithm to generate planar polygonal patches for building facades and the surrounding ground (Schmittwilken et al., 2009). The proposed method employs local neighborhood features and attribute grammar (e.g., object partonomy and observable geometric constraints) through Conditional Random Fields (CRFs) to classify these patches into facade, window, door, and staircase categories. Schmittwilken and Plümer proposed a top-down approach for reconstructing triple-run staircases from point cloud data. The method utilizes an attribute grammar formulation based on geometric dependencies for designing 3D models and subsequently employs the RANSAC paradigm for model selection and extraction of geometric parameters of each 3D object (Schmittwilken and Plumer, 2009). Oßwald et al. developed a plane segmentation method to detect vertical and horizontal planes and extract their geometric parameters for reconstructing 3D models of stairs using point clouds captured by humanoid robots (Oßwald et al., 2011).

Sanchez and Zakhor proposed a method that uses principal component analysis (PCA) to separate inclined planes of staircases. The method then uses the RANSAC algorithm to extract six parameters (number of steps, reference point, depth of the tread, riser height, width of the step and azimuth) to create a 3D model of stairs (Sanchez and Zakhor, 2012). Sinha et al. presented a data-driven approach that uses a minimal 3D map representation and calculates step-like local features using point neighborhoods to detect stairs (Sinha et al., 2014).

Perez-Yus et al. proposed a stair detection and modeling method that uses the depth-sensing capabilities of RGB-D cameras to segment and classify various elements in the scene. The proposed pipeline utilizes the Region-Growing strategy and common plane fitting algorithms, including the Hough transform and RANSAC, to segment the scene and extract information about the location, orientation and number of steps of the staircase (Perez-Yus et al., 2015).

Westfechtel et al. proposed a plane-based staircase detection method that utilizes a 3D graph concept to identify staircase structures within a point cloud. The method employs multiple ways to initialize the graph, enabling robust detection of staircases even if parts of the staircases are occluded (Westfechtel et al., 2018). Li et al. proposed a step plane detection method for the 3D reconstruction of staircase structures. The algorithm initially employs the NDT-RANSAC plane-filter and Region Growing plane-extraction methods to segment large-area planes. Next, the stair parameters (e.g., length, width, height, and number of steps) are extracted using an arithmetic progression calculation in the stair area (Li et al., 2018).

Yang et al. proposed a bottom-up hierarchical semantic classification method. This method uses semantic definitions, such as the planarity of the wall, ceiling, and floor surfaces, to establish relationships between the staircase connection spaces and the indoor spaces. For coarse segmentation of staircase points, the height histogram of points identifies the void regions between the planar surfaces of solid slabs and the connection space with stairs. The connected component algorithm then clusters distinct pieces, planes, and staircase clusters. Finally, the α-shaped algorithm constructs the surface model for each step of the staircase (Yang et al., 2019).

In the realm of utilizing AI methods for scene understanding and separation of staircase points, Chun et al. proposed an automatic pipeline to create digital staircase models from the point cloud using an AI method. The proposed pipeline includes the predictor's training procedure and the entire staircase detection and modeling process, which specifically uses the PointNet++ architecture as the backbone network for the instance segmentation task (Chun et al., 2024).

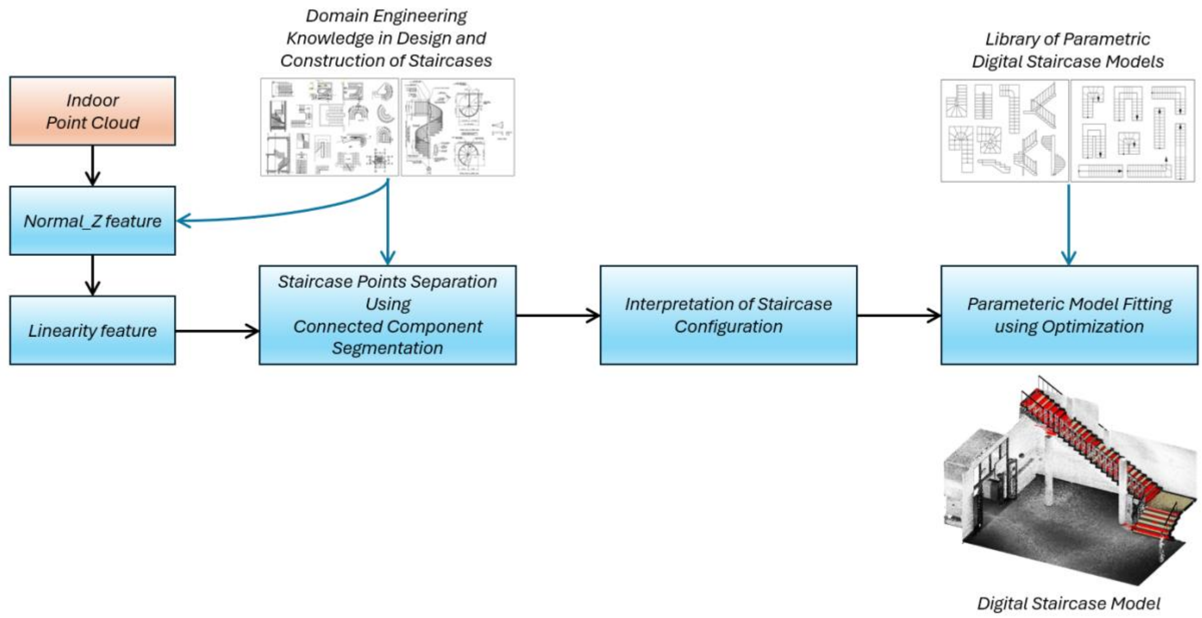


Figure 1: The proposed hybrid bottom-up, top-down workflow for creating digital staircase models using point cloud.

2.3 Research gap

Over the past decade, the creation of semantic digital building models and the digitization of built world assets has become feasible using multi-sensor remote sensing technologies. Raw point cloud data can be transformed into usable information for human and machine interpretation using advanced methodologies and techniques in computer vision and computational modeling. However, this process remains particularly challenging for staircase structures due to their diverse shapes and designs. In addition, unfavorable sensor positions often exacerbate these difficulties, leading to significant portions of the staircase being occluded or sparsely captured.

The point cloud data are unstructured and contain numerous objects and various planes. Hence, the data-driven methods developed for staircase detection and modeling still lack optimal performance. These methods result in creating digital models with inconsistent geometry and frequently necessitate extensive manual tuning of parameters to achieve accurate staircase detection. The model-driven approaches developed for creating digital staircase models also necessitate exploring numerous existing rules and constraints to formulate the staircase geometric model with high logical consistency. Achieving accurate digital representations requires meticulous consideration of these factors to effectively capture the nuanced complexities of real-world staircases. However, this task is particularly challenging due to the wide variety of staircase designs and configurations in diverse built environments.

Although the substantial growth of AI and machine learning (ML) concepts has yielded promising results in semantic understanding tasks, particularly in separating the main structural elements within point clouds, the efficiency of AI methods heavily relies on the diversity and completeness of training datasets. In this regard, collecting a large amount of annotated point cloud data for buildings, including staircase structures that are sufficiently diverse and complete, can be costly and time-consuming.

In this research paper, we aim to leverage the advantages of bottom-up and top-down approaches to create highly consistent digital staircase models with various geometric shapes and configurations. The objective is to utilize existing domain knowledge in design and construction to develop an automated framework for separation, design, and the parametric model fitting of staircase structures from point cloud data. Further insights into the proposed methodology will be provided in the following sections.

3. PROPOSED METHOD

As shown in Figure 1, the proposed hybrid bottom-up, top-down workflow for the automatic creation of digital staircase models using point clouds consists of three major steps: 1) staircase point separation, 2) design of digital parametric staircase models, and 3) model fitting through optimization. The details of each step are provided in the following subsections.

3.1 Staircase points separation

Staircase structures in the built environment are designed with specific inclination angles, influenced by factors such as building codes, architectural styles, and their intended function. Based on domain knowledge, typical staircases are designed with an incline between 30 and 37 degrees, aligning with recognized standards to ensure both safety and usability (International Building Code, 2021). Specifically, occupational safety standards recommend an angle of inclination between 30 and 50 degrees for fixed industrial stairs, with a preferred range of 30 to 35 degrees for indoor staircase environments (Occupational Safety and Health Administration, 2023).

In the proposed method, the *Normal_Z* feature is utilized to distinguish inclined staircase points from other building elements such as vertically oriented walls and horizontally oriented ceilings and floors within the point cloud (Figure 2b). To compute the normal vector values for a point in the point cloud space, the covariance matrix and the eigenvector values of its nearest neighboring points are calculated and analyzed (Chehata et al., 2009). This process involves determining the covariance matrix c for a given point p using Equation 1:

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

where k denotes the number of neighboring points within a sphere of radius 25 cm, and p_i and p refer to the 3D coordinates of the points under consideration. Furthermore, eigenvalues and eigenvectors are determined using Equation 2:

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

where λ and $\vec{v}_j$ denote the eigenvalues and eigenvectors, respectively. To determine the direction of the normal vector for each 3D point within the point cloud space, a predefined viewpoint is necessary. In this regard, the *+Z* axis serves as the reference, establishing the orientation of surfaces relative to this downward direction.

As can be seen in Figure 2c, the points corresponding to perfectly horizontal surfaces display a *Normal_Z* value of zero, while the points on vertical surfaces show the highest *Normal_Z* value, which is one. In this regard, the inclination angle of the staircase surfaces to the horizontal plane (θ) can be related to the *Normal_Z* using Equation 3:

$$Normal\_Z = Cos(\theta) \quad (3)$$

According to domain knowledge and recommended inclination angles for designing staircase structures, points with *Normal_Z* values ranging from "0.79" to "0.99" are selected. This selects points on the surfaces with an inclination angle of up to 30 degrees. (Figure 2d). Although the method effectively separates inclined staircase points, the output may also include edge points of walls, ceilings, and floor elements represented as lines, noise, and clutter. To mitigate this issue, the Linearity feature is used to isolate only the staircase surface points (Figure 2d). The Linearity feature is computed for each point within a spherical neighborhood of 25 cm radius using Equation 4:

$$Linearity = \frac{\lambda_1 - \lambda_2}{\lambda_1} \quad (4)$$

According to the histogram of Linearity values, edge points, noise, and clutter consistently exhibit higher Linearity values compared to the points of inclined staircase surfaces. In this regard, the mean value of the Linearity feature distribution (μ) is calculated, and points with Linearity values lower than μ are extracted as staircase points (Figure 2f). This selection includes points corresponding to staircase steps, risers, treads, and parts of railings (Figure 2g). Finally, to segment staircase instances within the environment into individual segments, the Connected Component Segmentation (CCS) algorithm is utilized (Figure 2h). This method involves setting a distance threshold and a minimum number of points per segment, thus identifying all connected points within the threshold as separate segments (Trevor et al., 2013). The approach effectively identifies and removes noise and outliers, typically manifesting as small or isolated segments in indoor scenes.

3.2 Design of digital parametric staircase models

3.2.1 Interpretation of staircase configuration

The architectural design of staircases typically features a series of stair flows and often includes two or more landing treads. The configuration and structural form of the staircases are fundamentally shaped by considerations such as the movement of people entering and leaving the space and the strategic positioning of the landing treads. In this context, the central parts of the staircase segments are analyzed to quantify the number of landing treads and determine the stair flows within the environment. As illustrated in Figure 3a, the extracted staircase segments lack points corresponding to the horizontal planes of the landing treads due to the filtering process described in Section 3.1. However, this data gap helps interpret the overall configuration of the staircase. To analyze the configuration of stairs, a 2D bounding box with a grid cell size of *d* is initially fitted to the stairs points in the X-Y plane. Subsequently, for any points present within the grid cells, the height value is replaced by the maximum height of the points within the grid cell (Figure 3b). This process eliminates the influence of noise points and ignores the uncommon inclined planes beneath the steps of the stairs during the model reconstruction step (Figure 3c). To detect the orientation of the staircase flows within the environment, the 3D density feature is computed for each point within a spherical neighborhood of a radius of 25 cm, and the central parts of the staircase are examined (Figure 3e). As illustrated in Figure 3f, this analysis reveals that the extracted staircase element comprises three flows and two landing treads, which run from left to right, top to bottom, and right to left, respectively.

3.2.2 Library of the parametric digital staircase models

The primary differences between the staircase instances lie in the number and size of the main components (such as steps, width, length, depth of steps, and landing treads) and the specific designs for flow rotation and landing tread placement. Specifically, four possible flow orientations are considered, labeled with numerical identifiers 1, 2, 3, and 4. These identifiers correspond to left-to-right, right-to-left, bottom-to-top, and top-to-bottom orientations, respectively (Figure 4a). The exact value of the identifiers indicates the flow of the stairs, the number of landing treads, and the placement of each landing tread. For instance, the primary configuration of the extracted staircase in Section 3.2.1 is represented by the array "142" (Figure 4b). This indicates that the staircase consists of two landing treads and three stair flows, positioned successively from left to right, top to bottom, and right to left. Accordingly, a library of parametric staircase models is generated based on the number of stair flows, landing treads, and their orientation within the environment. The library has multiple parametric prototype models for staircase types up to two landing treads. These prototypes can be systematically extended to more comprehensive models with three or more landing treads. Figure 5 shows a subset of this library.

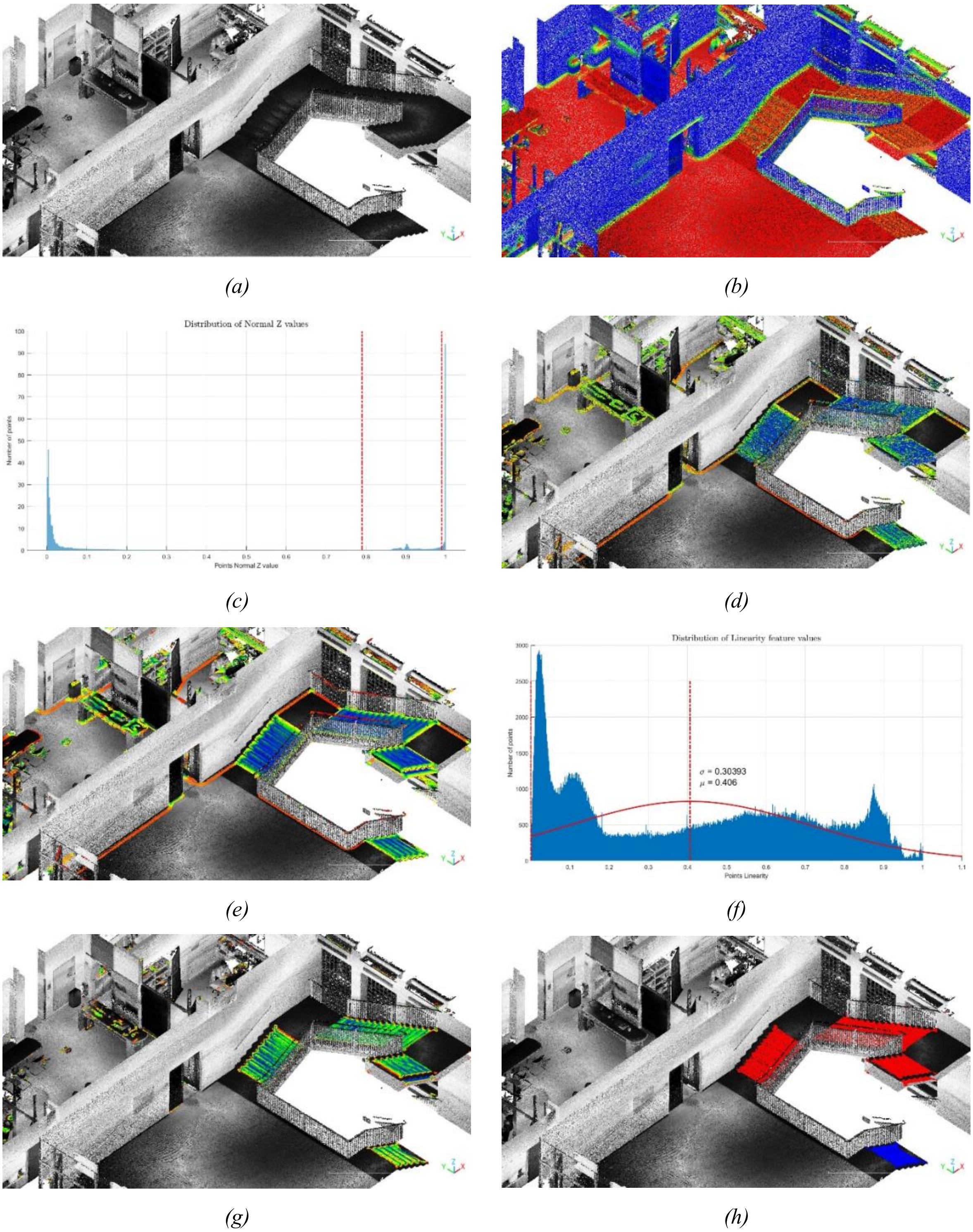


Figure 2: Staircase points separation: (a) original point cloud, (b) Normal_Z feature calculation, (c) histogram of the Normal_Z values, (d) filtering the points with the Normal_Z values between 0.79 to 0.99 (slopes ranging from 0.01% to 0.37%), (e) Linearity feature calculation, (f) histogram of the Linearity values distribution, (g) filter edges, noise, and unwanted furniture points using μ of the Linearity values, (h) separation of the individual staircase segments using CCS algorithm.

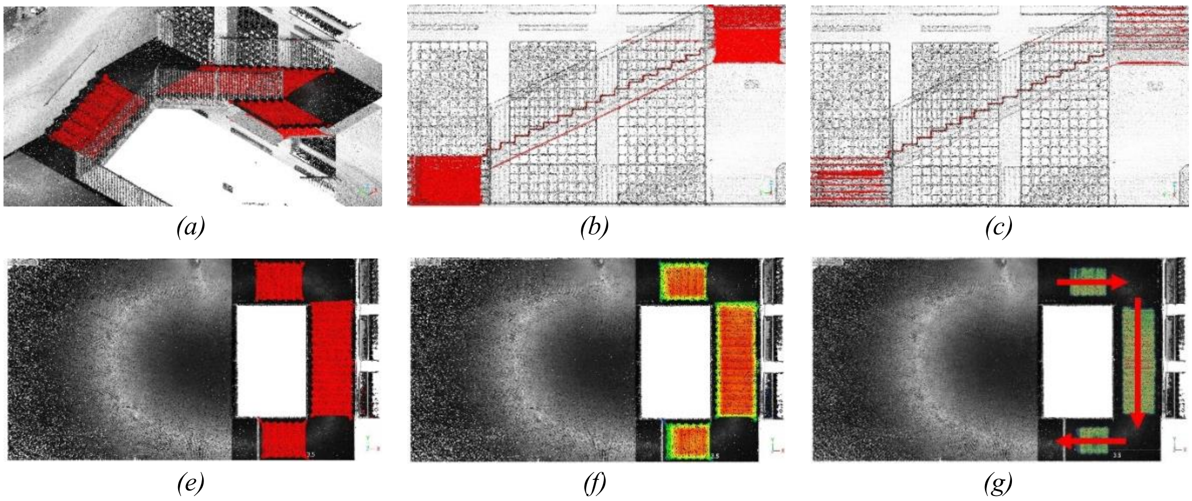


Figure 3: Interpretation of staircase configuration: (a) extracted staircase points, (b) the staircase points projected on Y-Z plan, (c) grid-based noise filtering and removing the uncommon inclined planes beneath the stair steps, (d) the staircase points projected on X-Y plan, (e) 3D point density feature calculation, (f) the detected stair flows.

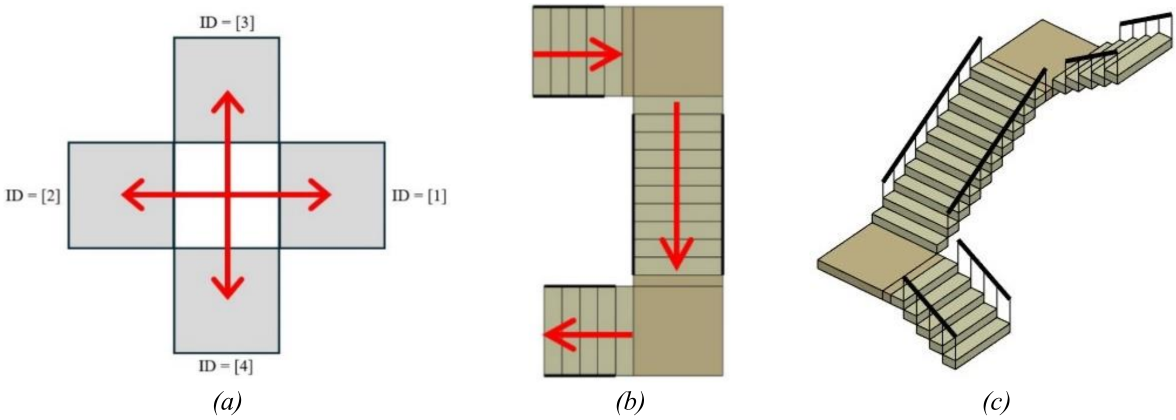


Figure 4: Determining the type of staircase based on the number of stair flows and the number of landing treads: (a) possible rotation orientations, (b) the configuration of the parametric model for the staircase instance with two landing treads and three stair flows with ID array of [1 4 2], and (c) design of the parameterized digital staircase model.

3.3 Model fitting through optimization

3.3.1 The parameters of the digital staircase model

The staircase structures typically comprise distinct components with unique values and dimensional attributes. Figure 6 shows an overview of the main components of a staircase structure. With laser scanning technology, only the visible surfaces of staircase components can be captured, not the parts that are obscured or internal. Therefore, the geometry provision and model reconstruction step focus on the visible parts. These include the stair tread (the horizontal part of the step), the stair riser (the vertical part between each tread), the landing treads (the flat platforms at the top or bottom of a staircase or between flights of stairs), the handrails (the rail for support) and the outer stringer (the structural component on the side of the staircase).

Table 1 presents the parameters required to create a digital staircase model using the proposed approach. These parameters are essential for accurately replicating the staircase structure in a digital format, ensuring that all critical dimensions and characteristics are captured for analysis or reconstruction purposes.

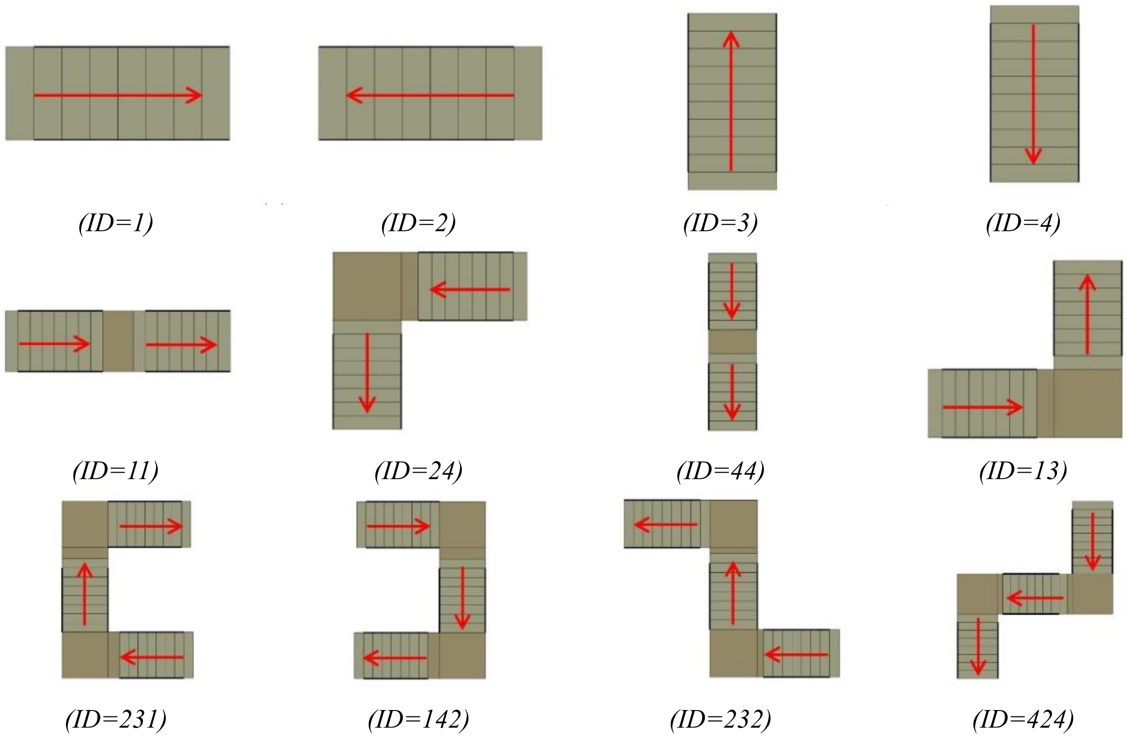


Figure 5: Subset of the library of parametric digital staircase models.

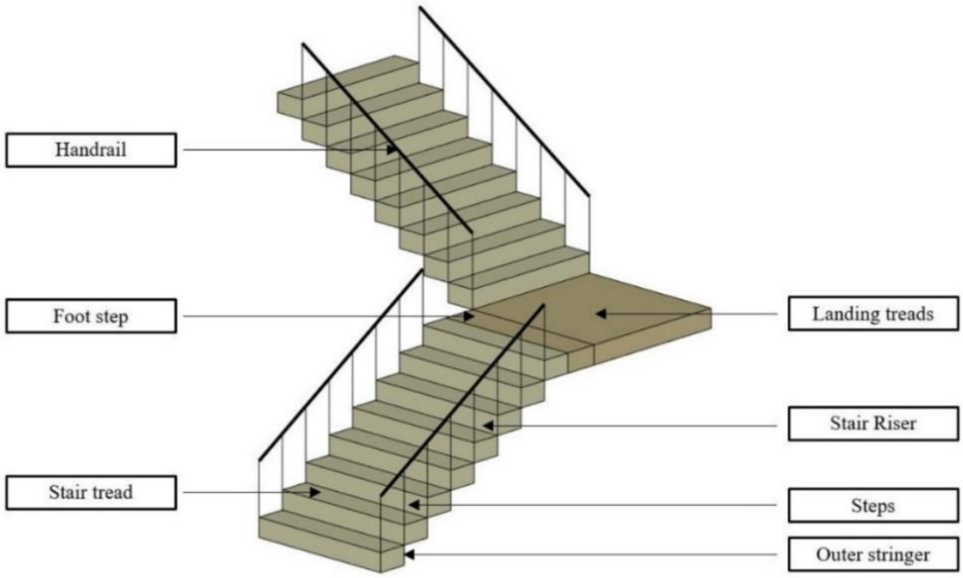


Figure 6: The components of a staircase with one Landing tread.

In other cases, such as curved, L-shaped with wider run, and spiral stairs, in addition to the parameters included in Table 1, the parameters related to the coefficients of the curvature equations of staircase structures are also added as unknown parameters in the model reconstruction process (Figure 7). These coefficients are specific to the mathematical equations of polynomial functions of the 2nd degree, spiral, and exponential functions, or circle equations. In this regard, the number of unknown parameters will vary depending on the mathematical function used and the specific configuration of the staircase. By incorporating these additional parameters, the model can more accurately represent the unique geometries of curved and spiral staircases, leading to a more comprehensive digital reconstruction.

Table 1: The parameters required for the creation of a digital staircase model with a single landing tread (Manhattan-world structure).

Parameters	
Number of steps	n
Height of steps	h
Width of steps	w
Depth of steps	d
Length of the landing tread	L
Centre point of the starting step	Xc, Yc, Zc

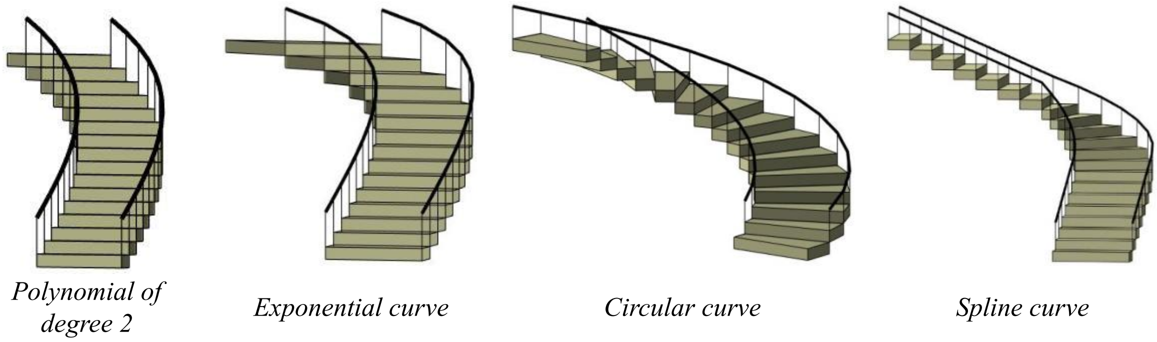


Figure 7: Representation of a non-rectangular staircase structures using various mathematical methods and equations.

$$y = ax^2 + bx + c \tag{5}$$

$$y = ae^{bx} \tag{6}$$

$$(x - x_c)^2 + (y - y_c)^2 = r^2 \tag{7}$$

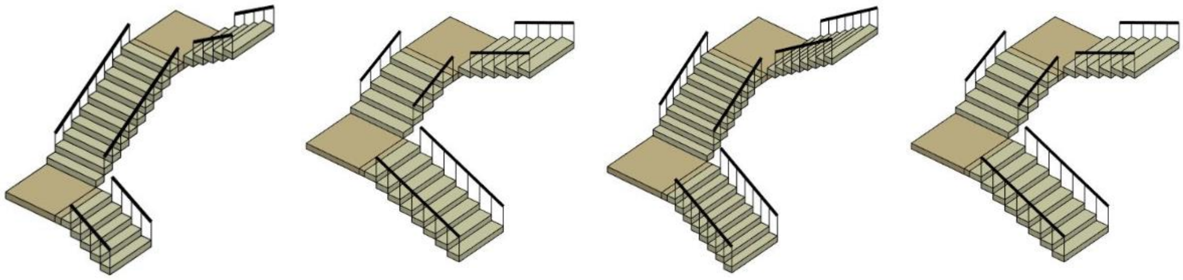
$$\begin{aligned} S_0(x) &= a_0 + b_0(x - x_0) + c_0(x - x_0)^2 + d_0(x - x_0)^3 \\ S_1(x) &= a_1 + b_1(x - x_1) + c_1(x - x_1)^2 + d_1(x - x_1)^3 \\ S_2(x) &= a_2 + b_2(x - x_0) + c_2(x - x_0)^2 + d_2(x - x_0)^3 \end{aligned} \tag{8}$$

3.3.2 Objective function definition

In the designed parametric staircase models using the proposed approach, specific rules and restrictions are established and applied to ensure that any change in the internal parameters of a component impacts all related elements (Figure 8). These rules and constraints are based on the principles of building design and construction, aiming to optimize the structure's functionality and aesthetics. Despite the consistent semantic topology, the designed parametric model might exhibit low geometric accuracy concerning the element's property values and the position of the entire staircase structure within the environment. In this regard, the selected raw parametric model is further refined by fitting to the point cloud data using the Nelder-Mead optimization method to extract optimal values for the model's parameters (Nelder and Mead, 1965).

The required model-to-point fitting objective function for the optimization process is defined by Equation 9:

$$Obj = min(\alpha \times G \ + \ \beta \times F\ ) \tag{9}$$



(a) (b) (c) (d)

Figure 8: Designing the parameterized digital staircase model; the process of changing the parameter values.

The term G refers to the distance between the points and the planes of the entire model, which is a critical factor for the vertical alignment of the parametric model toward the staircase points. This term is defined by Equation 10:

$$G = \sum_{i=1,j=1}^{n,k} |p_i - plane_j| \tag{10}$$

where the p_i is the staircase point i, $plane_j$ is the jth plane of the parametric model.

Also, the term F is related to the number of steps present within each stair flow connecting the landing treads, as well as the placement of the parametric model planes on the staircase points on the X-Y plane. This term is defined by Equation 11:

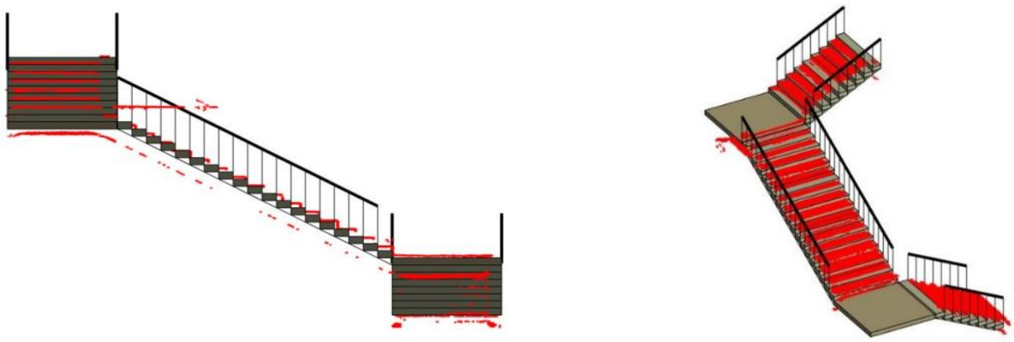
$$F = |p_{stairs} - \sum_{i=1}^{steps} p_{in}| \tag{11}$$

where 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.

The terms G and F represent values from two different aspects, with a significant difference in their values. To balance the impact of both terms on the overall objective function, the α and β coefficients are considered. These coefficients are also optimized to ensure that the influences of G and F terms are balanced in the final objective function. In addition, creating excessive steps during the optimization process may not change the overall distance value between the steps and the model planes. To address this problem, 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 G term:

$$if\, p_{in} == 0 \quad then \quad Obj = (\alpha \times G + \beta \times F) + 10000 \tag{12}$$

As mentioned in Section 3.3.1, a non-rectangular staircase structure can also be created by a mathematical method and equation (e.g., polynomial of degree 2, exponential curve, and circular equation). In this regard, the exact type of staircase is selected after the model fitting process and the comparison between the overall objective function values of the parametric models being tested.



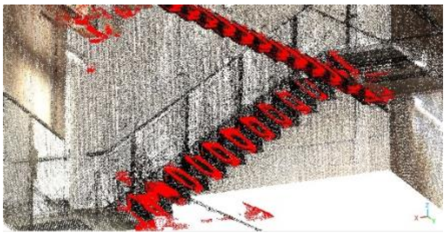
(a) (b)

Figure 9: Fitting parametric staircase model to points; (a) Vertical alignment of the parametric model toward the staircase points (term G), (b) placement of the parametric model planes on the staircase points (term F).

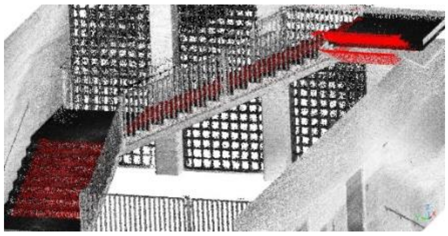
4. EXPERIMENTAL RESULTS

4.1 Case study

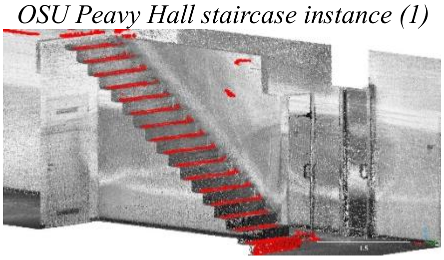
In this paper, eight different staircase instances are considered to evaluate the performance of the proposed method for the automatic creation of digital staircase models from dense laser scan point clouds (Figures 10-11). These datasets are from five different buildings located at Technical University of Munich and Oregon State University campuses and include staircases with both rectangular and non-rectangular configurations. A detailed summary of the pertinent properties of the input data, including the dimensional information and the number of points, is provided in Table 2. The proposed pipeline is implemented in Python and MATLAB on a desktop computer (11th Gen Intel(R) Core(TM) i7-1165G7, with 16.0 GB of memory). The evaluation metrics considered various aspects of the proposed method, including accuracy, efficiency, and scalability regarding the geometry and semantics. This comprehensive analysis provides insights into the practical implementation of the proposed method for the automatic creation of digital staircase models in the built environment.



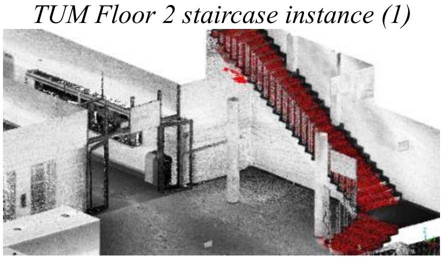
OSU Peavy Hall staircase instance (1)



TUM Floor 2 staircase instance (1)

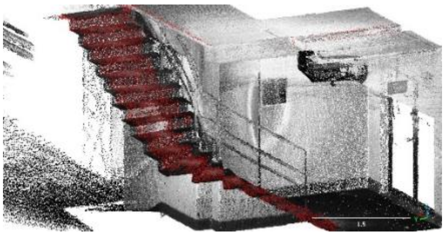


TUM Floor 2 staircase instance (3)

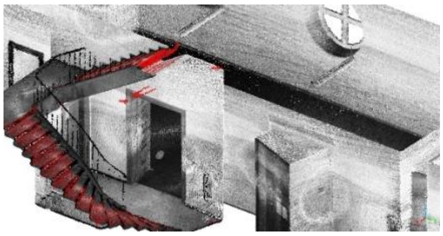


TUM Floor 4 staircase instance (1)

Figure 10: The results of the staircase points separation on the test data using the proposed method (rectangular configuration).

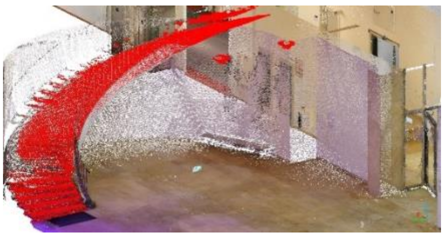


OSU Peavy Hall staircase instance (1)



TUM Floor 2 staircase instance (1)

TUM Floor 2 staircase instance (3)



TUM Floor 4 staircase instance (1)

Figure 11: The results of the staircase points separation on the test data using the proposed method (non-rectangular configuration).

Table 2: Overview of data used in this research.

Dataset	Length (m)	Width (m)	Number of points	Number of staircase
OSU Peavy Hall	6.66	3.25	612.530	1
TUM Floor E	12.09	5.12	113.112	1
TUM Floor 2	16.31	46.00	1.057.295	3
TUM Floor 4	18.26	32.88	13.239.024	1
TUM Entrance	19.58	34.94	10.027.980	2

4.2 Implementation

This paper presents an automated pipeline for creating parameterized digital staircase models from raw laser scan point clouds. The proposed method does not require point cloud features, such as intensity, depth, or RGB values, as input. It utilizes XYZ values only for separating inclined staircase points and creating a subsequent parametric digital staircase model. Additionally, to improve processing efficiency, the input point clouds are initially uniformly subsampled using a grid size of 2.5 cm. This reduces the processing time for calculating *Normal_Z* values and Linearity features for the separation of inclined staircase points. Thus, the proposed method is well-suited for effectively processing data with similar point densities.

According to the proposed pipeline, the *Normal_Z* feature is first calculated for any point within the point cloud, considering a sphere neighborhood with a radius of 0.25 cm. The points belonging to the inclined surface with *Normal_Z* values between 0.79 and 0.99 are then separated. As mentioned in Section 3.1, the results include noise and clutter points. To address this, the Linearity feature is calculated for each point, considering again a sphere neighborhood with a radius of 0.25 cm, to detect noise and boundary points between the ceiling, floor, and wall elements. Finally, the CCS method is employed to segment the points belonging to individual staircase instances. In the proposed pipeline, the maximum neighborhood distance for the CCS method is the only parameter that can affect the separation of inclined staircase points and the subsequent digital model reconstruction process, specifically in the creation of the digital model for the landing tread elements. Setting a default value for this parameter depends on the configuration of the staircases and the distance between the landing treads. During the implementation of the algorithm for the test data, the maximum neighborhood distance value is set to 0.5 m and the minimum number of points to segment each staircase instance is specified as 2500. These parameter values are selected experimentally, and their effect on the results is investigated in Section 4.3.1.

After separating the staircase instances, the central parts of the staircase points are examined using the 3D point density feature. The configuration design for each staircase is then determined. Subsequently, the corresponding digital parametric models are selected from the library of parametric prototype models using the configuration ID arrays introduced in section 3.2.2. These models integrate various parameters (such as the number of steps between landing treads and the dimensions of the geometric properties (including width, depth, and height) and consider contextual relations between components. This preserves the semantic relationships between the components of the staircase and ensures geometric consistency. To extract optimal parameter values for the digital models and make them resemble real-world structures, the selected digital parametric models are fitted to the extracted staircase points using the optimization process described in the Section 3.3. Table 3 presents the values of the optimization parameters used for creating the parameterized staircase models.

Table 3: The values of parameters used for the optimization process.

	Parameters		
Problem	Tolerance-X	Tolerance-Obj	Iterations
Volumetric digital model fitting	0.0001	0.0001	300

4.3 Results and Evaluation

4.3.1 Experimental results on staircase points separation

To assess the effectiveness of the proposed method for accurate separation of the staircase points, the manually annotated ground truth data is compared with the results of the staircase point separation. For each dataset, the standard quality metrics of recall, precision, and F-score for the extraction of staircase points from other building elements are calculated using equations presented in 13-15 where TP, TN, FP, and FN are True Positive, True Negative, False Positive, and False Negative, respectively.

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

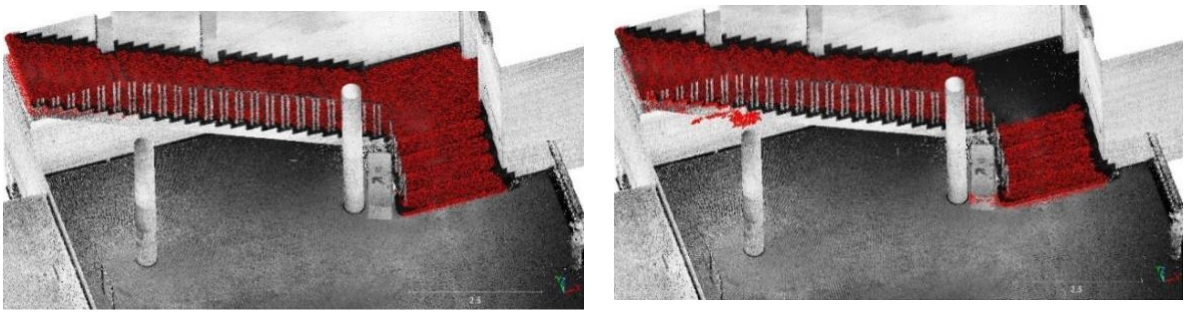
$$Recall = \frac{TP}{TP+FN} \quad (14)$$

$$F - score = 2.\frac{Precision.Recall}{Precision+Recall} \quad (15)$$

According to the results reported in Table 4, the overall accuracy value for separating staircase points from other elements is about 93\%. This underscores the performance of the proposed pipeline for the automatic separation of staircase points with any design configuration, including those with rectangular and non-rectangular types. However, the overall recall value for separating the staircase points from other elements is about 79\%. This value is influenced by multiple factors. Primarily, the filtering process that utilizes the *Normal_Z* value to separate inclined staircase points excludes the points corresponding to the landing tread planes (Figure 12b). This exclusion substantially impacts the accuracy. Additionally, the proposed method does not possess the capability to detect and separate railing points. These limitations collectively contribute to the relatively low overall accuracy value. Among all datasets, OSU Peavy Hall data has achieved the lowest recall value for separating staircase points. This is likely due to utilizing stationary 3D scanners to collect data, which result in occlusions in step treads and riser parts of the captured point cloud. This problem can introduce errors in calculating the geometric features, subsequently resulting in errors in separating and filtering inclined staircase points (Figure 13c).

Table 4: The results of staircase points separation on building datasets.

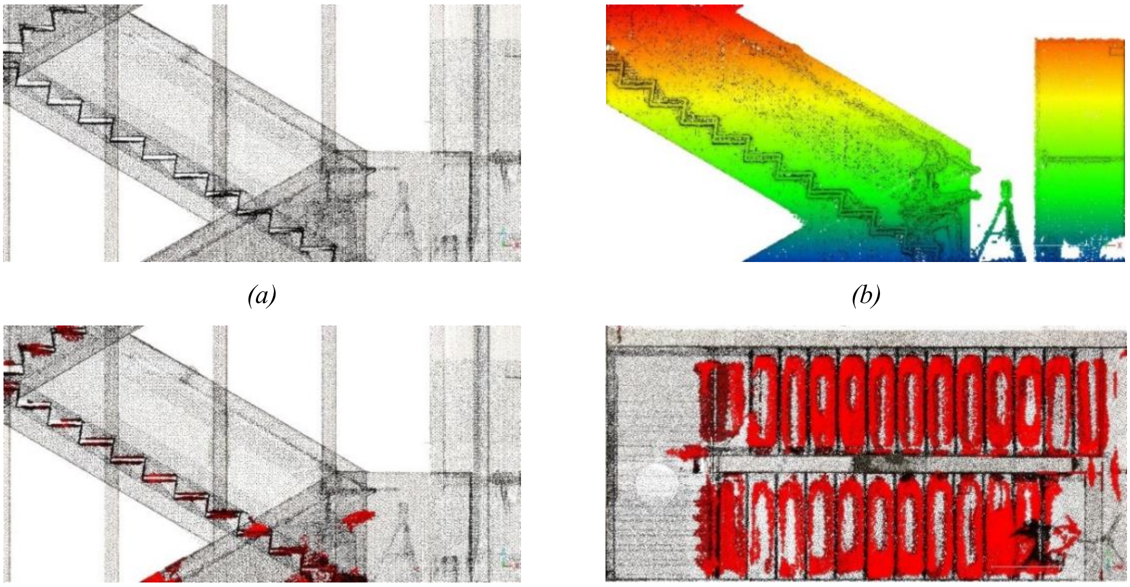
	Precision		Recall		F1-Score		Accuracy
Dataset	other	stair	other	stair	other	stair	
OSU Peavy Hall	0.82	0.09	0.94	0.02	0.88	0.04	0.79
TUM Floor E	0.97	0.83	0.98	0.71	0.98	0.77	0.96
TUM Floor 2	0.96	0.86	0.99	0.55	0.98	0.67	0.96
TUM Floor 4	0.99	0.92	0.99	0.81	0.99	0.87	0.99
TUM Entrance	0.99	0.86	0.99	0.78	0.99	0.86	0.99
Overall	0.94	0.71	0.97	0.62	0.96	0.64	0.93



(a) *(b)*

Figure 12: The result of staircase point separation for TUM Floor 4 data: (a) the ground truth for staircase points separation, (b) the result of staircase points separation using the proposed method.

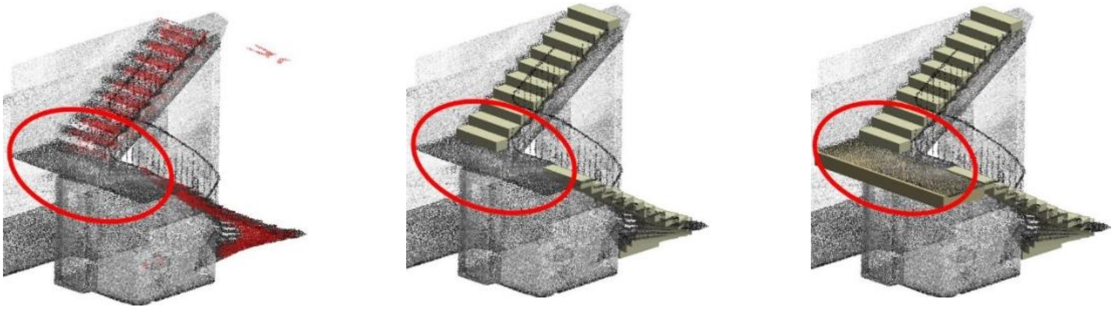
As mentioned in Section 3.1, the maximum neighborhood distance in the CCS method plays a critical role in distinguishing individual staircase instances. For the TUM Floor 2 staircase instance (2), the chosen value for this parameter led to errors in segmenting the entire staircase. Specifically, setting the maximum neighborhood distance to 0.5 m resulted in over-segmentation treating each stair flow as a separate staircase (Figure 14a). In general, the significance of this parameter depends on the staircase configuration, as well as the position and dimensions of the landing treads.



(a) *(b)*

(c) *(d)*

Figure 13: Error in separating staircase points in OSU Peavy Hall data: (a) the raw point cloud data, (b) the structure of the captured point cloud (including occlusions), (c) the result of the separated staircase points from side view, (d) the result of the separated staircase points from top view.

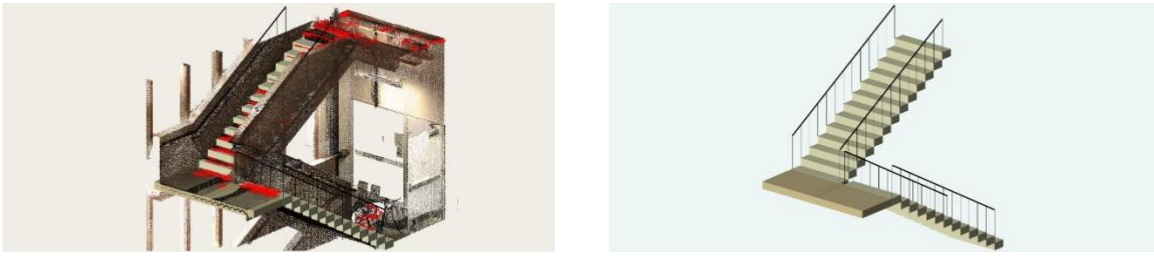


(a) *(b)* *(c)*

Figure 14: The effect of the maximum neighborhood distance parameter value on the result of digital staircase model creation for TUM Floor 2 staircase instance (2): (a) separated staircase instances, (b) the result of digital staircase model creation using the proposed method, and (c) correct placement of the landing tread elements in the reconstructed digital staircase model.

4.3.2 Experimental results on digital staircase creation

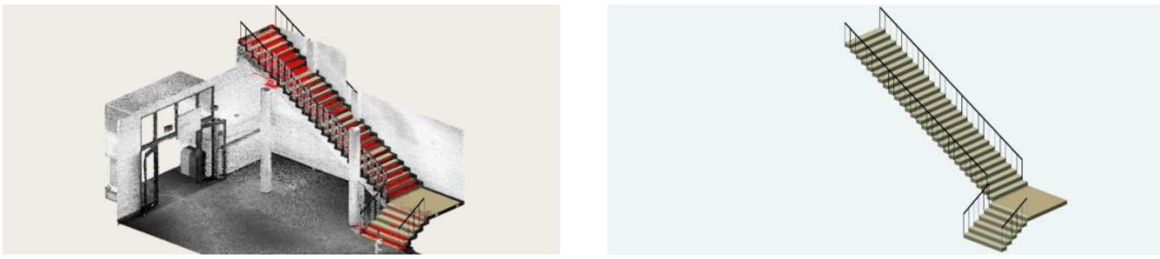
Figures 15-16 illustrate the result of the model fitting process and the creation of parametric digital staircase models using point cloud data. As discussed in Section 3.3, the selection of the appropriate configuration for the parametric digital model of non-rectangular staircase structures is based on comparing objective function values obtained by testing various mathematical equations. Figure 17 shows the process of fitting various parametric digital models and the corresponding objective function values for the TUM Floor E staircase instance (1). In this regard, fitting the parametric digital staircase model with a spline curve configuration has achieved the lowest overall objective function value compared to other tested configurations of the parametric digital staircase model. Thus, the parametric digital staircase model with a spline curve configuration is considered the proper model for representing the TUM Floor E staircase instance.



OSU Peavy Hall instance (1)

TUM Floor 2 staircase instance (1)

TUM Floor 2 staircase instance (3)

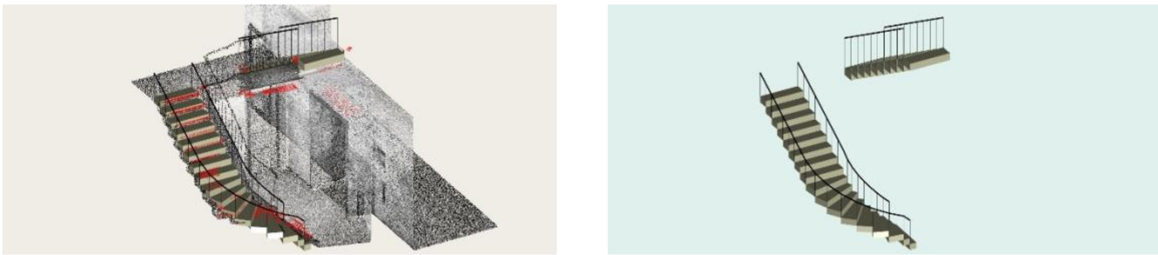


TUM Floor 4 staircase instance (1)

Figure 15: The reconstructed digital staircase models for the test data using the proposed method (rectangular configuration).

To evaluate the performance of the proposed approach for creating digital staircase models, a quantitative comparison is made between the parameters of the components (e.g., number of steps, dimensional values, etc.) in the reference models and those in the reconstructed digital models. The standard metric of mean error for each dataset is presented in Table 5. In addition, for each dataset the distance between the model and the points of the staircase is measured. The value indicates the closeness of the reconstructed model to the captured point cloud. The overall mean accuracy of about 5 cm in the estimation of dimensional parameters and 87\% relative accuracy in estimating the number of steps demonstrate the effectiveness of the proposed method for the automatic creation of digital staircase models in the built environment.

TUM Floor E staircase instance (1)



TUM Floor 2 staircase instance (2)

TUM Entrance staircase instance (1)

TUM Entrance staircase instance (2)

Figure 16: The reconstructed digital staircase models for the test data using the proposed method (non-rectangular configuration).

Despite the low recall value for separating the points of the stairs in the OSU Peavy Hall data, the proposed method estimated the parameters of the corresponding digital staircase model with 10 cm precision. Also, considering the significant presence of clutter and obstruction in the TUM Entrance data, the proposed parametric modeling approach created a parametric digital staircase model with consistent geometry. This underscores the capabilities and advantages of the proposed top-down approach, which utilizes the parametric modeling process to create detailed digital models with consistent geometry.

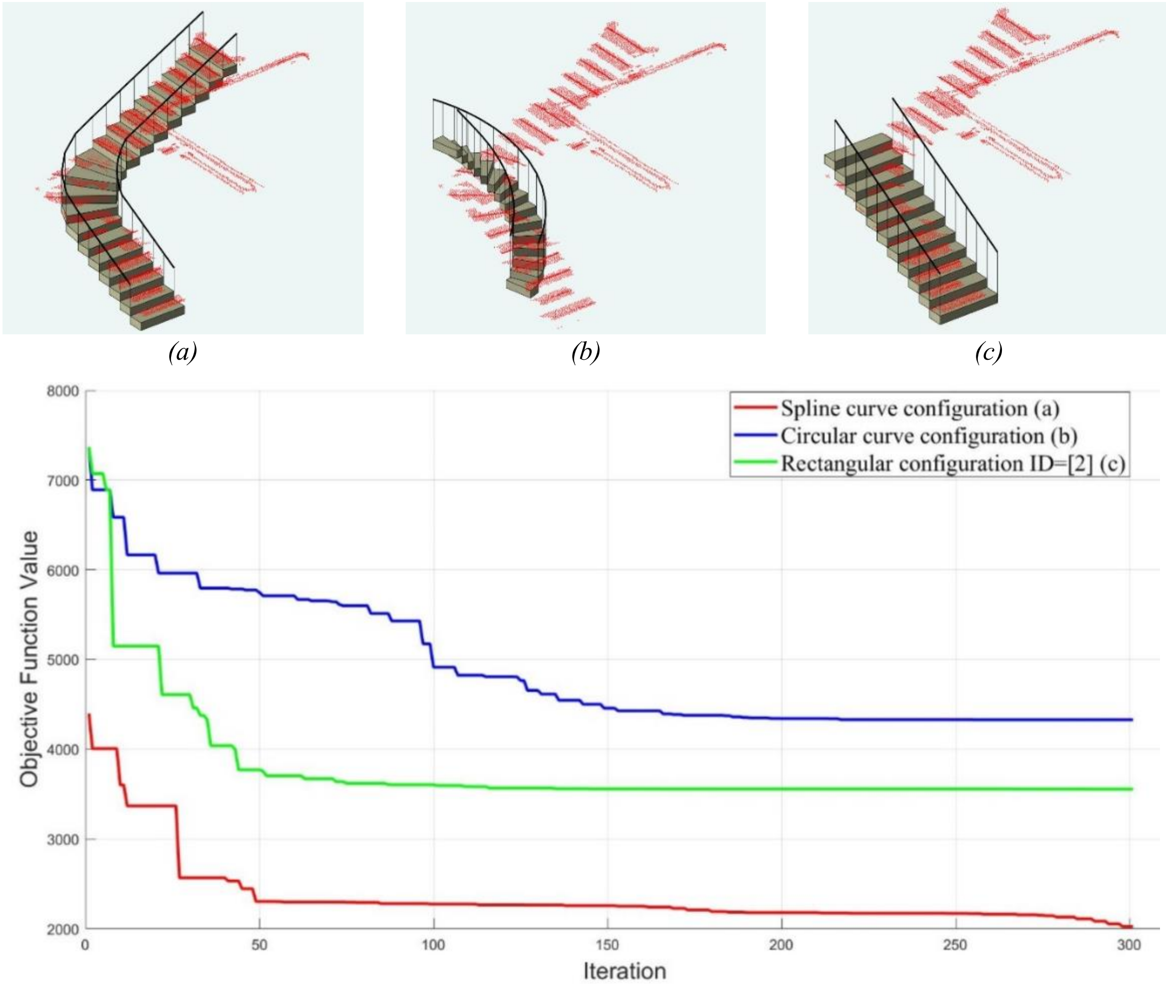


Figure 17: Fitting various parametric digital models to the TUM Floor E staircase instance (1) points, (a) spline curve configuration, (b) circular curve configuration, (c) rectangular curve configuration, and (d) the comparison between the corresponding optimization process and overall objective function values.

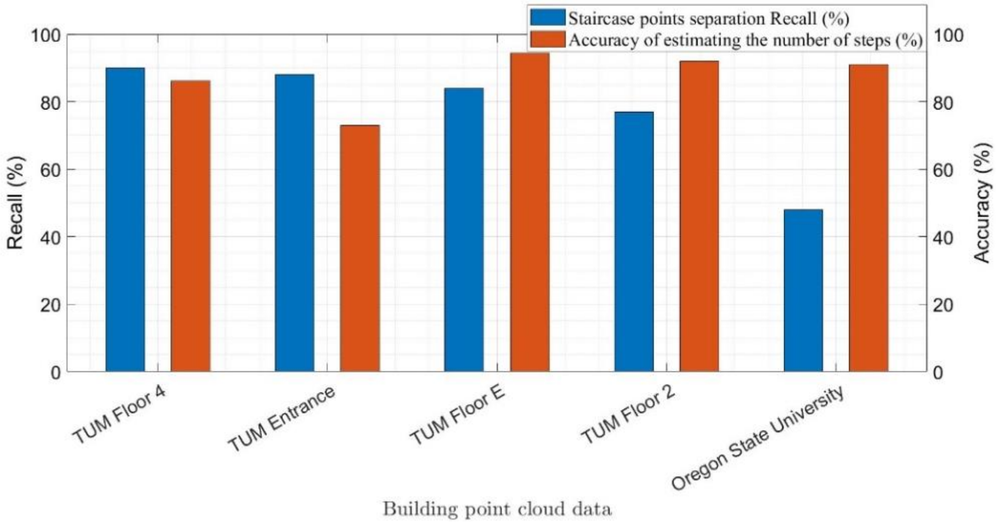
Table 5: Accuracy evaluation of digital model reconstruction (the values for the reported parameters in the table are all in cm).

Dataset	OSU	TUM F(E)	TUM F(2)	TUM F(4)	TUM Entrance
Steps:					
Width	20	3	5	5	5
Depth	2	1	4	5	2
Height	1	1	2	3	2
Number of Steps	91.6%	94.4%	92%	86.2%	73.46%
Landing treads:					
Width	20	-	4	5	-
Depth	5	-	2	5	-
Overall accuracy	10	2	3	5	3
Model to Points	8	35	13	2	16

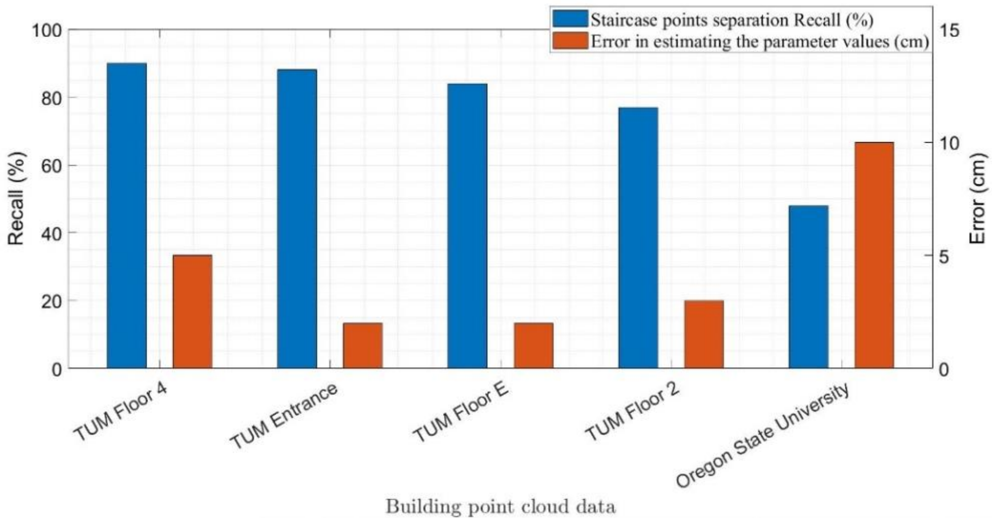
One of the critical factors influencing the accuracy of the reconstructed digital staircase model is the accuracy of separated staircase points. The proposed bottom-up approach for separating inclined staircase points relies on geometric features, such as *Normal_Z* component and Linearity. However, the accuracy of calculating these geometric features within a specific neighborhood depends on the staircase's inherent geometry and configuration, and the environment. In certain cases, using diverse materials, components, or specific design choices can introduce errors in calculating the exact geometric feature values. These inaccuracies can lead to errors in correctly separating the inclined staircase points, which in turn affects the overall accuracy of the digital model reconstruction. Although the parametric modeling approach can handle noise and gaps in the data, the ultimate accuracy of the resulting digital model is still contingent on the quality of the input data and the extent of errors present. Figure 18 illustrates the histograms of the recall values achieved in separating the stair points and the accuracy of estimating the dimensional parameters and number of steps. According to Figure 18b, there is a linear relationship between the accuracy of estimating the dimensional parameters and the recall value in separating staircase points. Specifically, as the recall value for separating staircase points decreases, the error in estimating the dimensional parameters increases.

Table 6: Quantitative comparison of the results between proposed parametric modeling approach and the data-driven model reconstruction algorithm.

Method	Number of Steps	Parameters	Points to Model
data-driven	93%	8 cm	9 cm
Proposed approach	87%	5 cm	15 cm



(a)



(b)

Figure 18: The Evaluating the impact of achieved recall value for separating staircase points on the accuracy of estimating the dimensional parameters and the number of steps: (a) histogram of the recall value and the accuracy of estimating the number of steps, (b) histogram of the recall value and accuracy of estimating the dimensional parameters.

4.3.3 Selection of the optimization method

This section presents a quantitative comparison between the selected Nelder-Mead optimization algorithm and particle swarm optimization (PSO) for minimizing the objective function in the model-fitting process (Kennedy and Eberhart, 1995). Figure 19 shows the histogram of the overall objective function values, digital model reconstruction accuracy, and processing time required to fit the digital staircase model for the OSU Peavy Hall dataset using various swarm sizes in the PSO.

Although PSO is a well-established meta-heuristic algorithm, the performance comparison revealed that Nelder-Mead offered comparable objective function values with lower computational costs. As shown in the histogram, increasing the swarm size in PSO slightly improved the objective function value. However, the computational time grew disproportionately without a corresponding gain in digital model reconstruction accuracy. This makes the Nelder-Mead method particularly advantageous regarding computational efficiency, especially for model-to-point fitting problems with time and resource constraints involving datasets ranging from thousands to millions of points.

Furthermore, the formulated optimization problem is more localized than global, due to prior knowledge of the feasible parameter ranges (e.g., step height and depth) derived from domain engineering expertise. This domain knowledge effectively constrains the search space, making the problem better suited to local optimization methods, such as Nelder-Mead, rather than requiring a global search.

Additionally, metaheuristic swarm-based algorithms, such as PSO, etc., require careful tuning of hyperparameters such as swarm size, inertia weight, and cognitive and social coefficients. The optimal configuration of these parameters can vary significantly between different datasets or problem scenarios, introducing an extra layer of complexity and potential for overfitting.

Nelder-Mead, being a local search method, has fewer hyperparameters to adjust, making it more straightforward and less sensitive to changes in problem-specific configurations. Despite the flexibility of PSO and other meta-heuristics in global search applications, Nelder-Mead's simplicity, automation, and efficiency in solving this specific problem justifies its selection. Therefore, Nelder-Mead can provide a higher level of automation with minimal user intervention. Considering the algorithm's stability in convergence, the required time for model-fitting, and the number of hyperparameters, Nelder-Mead is selected, while other optimization algorithms can also be utilized.

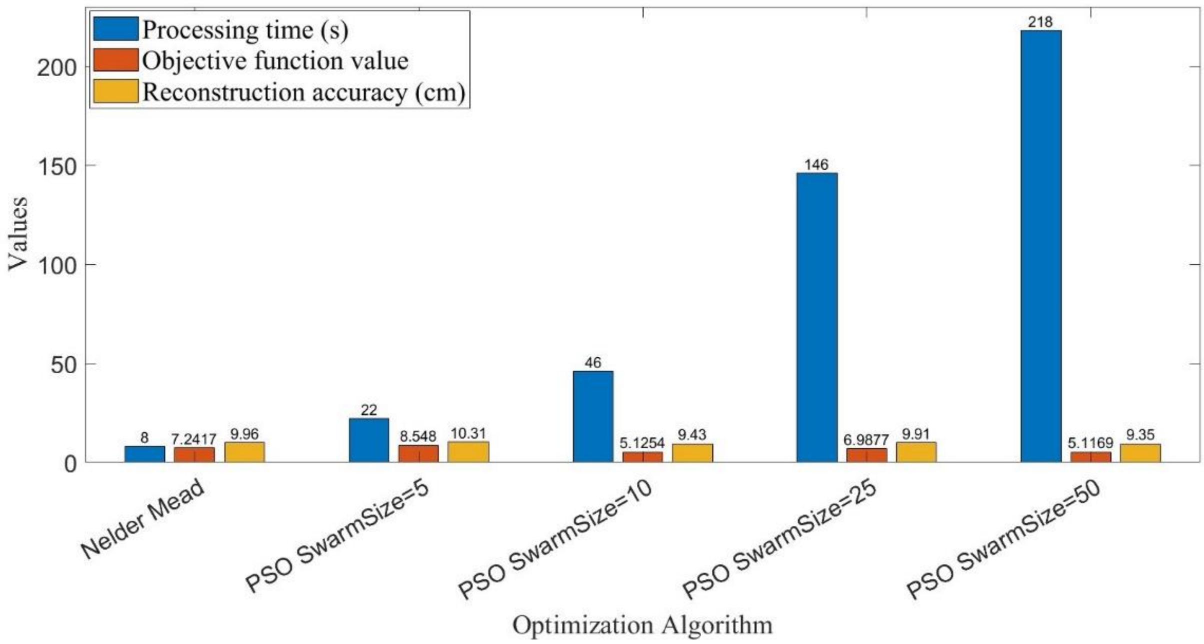
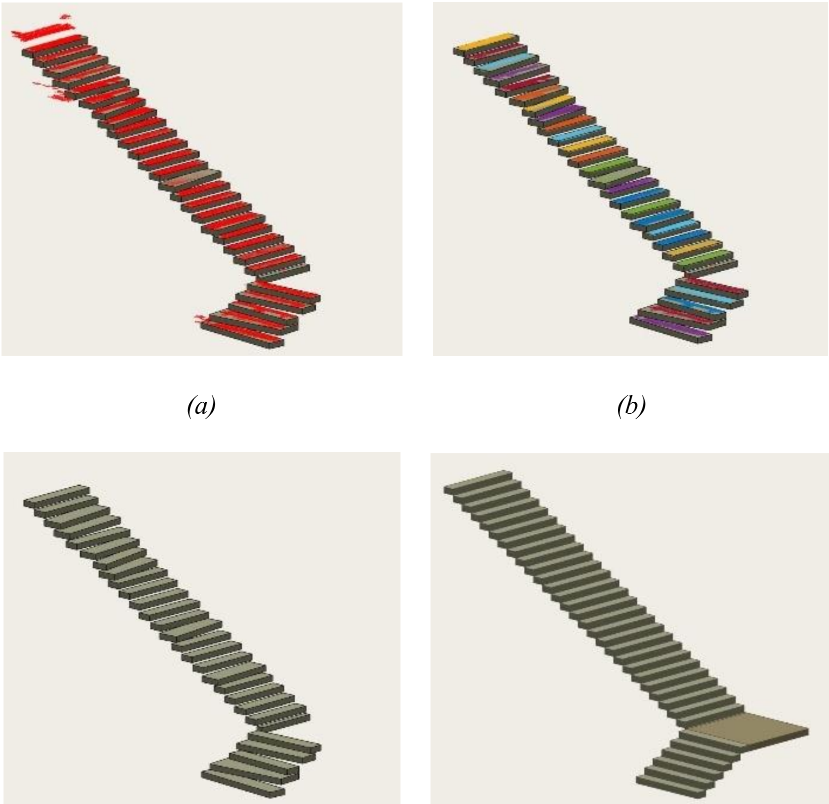


Figure 19: Evaluating the impact of the selected optimization algorithm on model fitting step: a quantitative comparison of overall objective function values, reconstruction accuracy, and the processing time required to fit the digital staircase model.

4.3.4 Comparison with other methods

In this section, a quantitative comparison is conducted to evaluate the performance of the proposed method in creating a digital staircase model from point cloud data compared to other algorithms developed for this purpose. This involves comprehensively examining our proposed parametric modeling approach compared to a solid data-driven method. After separating the inclined staircase points and individual staircase instances, the data-driven method employed for this purpose requires separating the stair tread of each step using RANSAC plane fitting algorithm (Figure 20a). Next, the 3D bounding box fitting algorithm is utilized to extract the dimensional values of each step (Figure 20b). The implemented algorithm is tested on all building point clouds in this study and the resulting digital models are compared with the corresponding digital models. This involves a comparison of the parameters of the corresponding reconstructed elements present in both digital staircase models.



(a) (b)

(c) (d)

Figure 20: The results of creating a digital staircase model for TUM Floor 4 data using the data-driven approach and the proposed parametric modeling approach include: (a) separated staircase points, (b) separation of stair tread planes using the data-driven method, (c) creation of the digital staircase model using the bounding box fitting algorithm, and (d) creation of the digital staircase model using the proposed parametric modeling method.

According to the results reported in Table 6, the implemented data-driven algorithm can create digital staircase models with an overall accuracy of 94\% in estimating the number of steps and a mean distance value of 9 cm for the model to points distance. However, the method has achieved a lower accuracy in estimating the value of the model parameters, with a mean error of 8 cm. As can be seen in Figure 20, the effectiveness of solid data-driven algorithms, such as the fitting of boundary boxes, depends on the quality of the data and often results in errors in estimating the dimensional parameters of the models and in creating digital models with inconsistent geometry. Addressing these issues requires the use of various thresholds and assumptions to correct the geometry and improve consistency between different parts of the models. Nevertheless, due to the use of a parametric modeling approach, the proposed method can consider the semantic relationships between different parts of the digital models, which helps manage poor data quality and ensures the creation of digital staircase models with consistent geometry.

Table 7 compares the key features of the proposed method with those of five state-of-the-art methods developed for the automatic creation of digital staircase models. This comparison explores various aspects and potential contributions of the proposed method, such as its robustness and generalizability for creating digital staircase models.

According to Table 7, most of the developed methods are capable of creating parametric digital staircase models. However, these methods mainly adopt a bottom-up reconstruction approach and are typically limited to staircases with rectangular configurations. Most bottom-up approaches use RANSAC plane fitting or the Region Growing method to segment staircase points from point cloud data (Table 8). While these methods are effective, they often require manual calibration and parameter tuning for different environments, which limits their level of automation. Furthermore, the creation of geometric models in these approaches heavily relies on data-driven techniques such as α-shapes or rectangular shape fitting. Given the complexity of indoor environments, occlusion and clutter, these data-driven methods face challenges in accurately representing geometric models and simulating topological relationships between components. Additional post-processing steps are usually required to adjust parameters, often using the mean of the extracted dimensions, which can introduce geometric inaccuracies.

Unlike conventional data-driven approaches, our proposed hybrid bottom-up, top-down approach incorporates domain engineering knowledge in the design and construction of staircases along with geometric feature calculation, allowing for segmenting the staircase instance with any configuration and design within various environments. The proposed model reconstruction method also employs parametric modeling concepts combined with an optimization process. This enables the creation of high-quality parametric digital staircase models with accurate semantics and proper relationships between components. Due to the flexibility of the parametric modeling approach in handling challenges such as noise and gaps in the data, the proposed reconstruction method achieves a high level of automation and robustness, without the need for parameter adjustment or additional post-processing steps. The proposed method can be used for all staircase instances in the built environment (rectangular and non-rectangular configurations) that follow the parametric modeling principles in their construction.

Table 7: Comparison of key features of the proposed method with five state-of-the-art methods.

Method	Proposed pipeline	Parametric modeling	Model fitting	Non-rectangular configuration
Schmittwilken et al., (2009)	Top-down, Bottom-up	✓	×	×
Schmittwilken and Plumer., (2009)	Top-down	✓	✓	×
Sanchez and Zakhor., (2012)	Bottom-up	✓	✓	×
Li et al., (2018)	Bottom-up	✓	×	×
Yang et al., (2019)	Bottom-up	✓	×	✓
Ours	Top-down, Bottom-up	✓	✓	✓

Table 8: Comparison of staircase detection and modeling steps across the state-of-the-art methods.

Method	Staircase detection	Model reconstruction
Schmittwilken et al., (2009)	Detect the planar patches using RANSAC, and classify them with CRFs based on local and semantic context	Applying an attribute grammar and AND-OR tree parsing to guide reconstruction using geometric and structural constraints
Schmittwilken and Plumer., (2009)	Estimate the normal vectors to define and classify the candidate regions	Use RANSAC for model selection, guided by an attribute grammar to encode object symmetry, composition rules, and geometric constraints
Sanchez and Zakhor., (2012)	Use the Principal Component Analysis (PCA) with normal vector calculation to segment points based on angle threshold, followed by Region Growing to improve the segmentation results	Use RANSAC to fit the geometric model and extract the parameters
Li et al., (2018)	Extract the staircase points using Normal Distribution Transformation (NDT) RANSAC method, followed by Region Growing to improve the segmentation results	Use RANSAC to fit the geometric model and extract the parameters

Yang et al., (2019)	Use the hierarchical semantic definition of indoor spaces to label floors and slabs, and separate the connecting staircase points between them	Use α-shapes method to extract the boundary points of stair steps, followed by post-processing to adjust the parameters
Ours	Knowledge-based staircase point separation using geometric features	Parametric model fitting using optimization

5. DISCUSSION

This paper presents a novel pipeline for the automatic creation of parameterized digital staircase models from raw laser scan point clouds. The result of the implementation of the proposed method across various indoor staircases with different configurations and designs demonstrates its effectiveness in creating coherent digital models with notable robustness and adaptability. The proposed method aligns domain knowledge in the design and construction of staircases with the parametric modeling approach, allowing for the consideration of different degrees of freedom to model a wide range of staircase models in the real world. The proposed hybrid bottom-up and top-down approach facilitates the effective integration of low-level geometric features with high-level semantic modeling, thereby enhancing both the consistency and interpretability of the resulting models.

The automation achieved by the pipeline significantly reduces the need for manual intervention, promises significant progress in the field of "Scan-to-BIM" and automatic creation of digital building models from raw point clouds . Moreover, the method's reliance solely on XYZ coordinates, without requiring intensity, RGB, or other auxiliary data, broadens its applicability across diverse scanning technologies and operational environments. Its capability to handle large, unstructured point cloud datasets of varying quality further underscores its potential for practical applications across various domains such as architectural modeling, heritage documentation, and facility management.

5.1 Limitations

Despite careful consideration, the proposed method for the automatic creation of digital staircase models from point cloud data presents certain limitations that may affect its applicability to a broader range of staircases with different configurations and designs.

The proposed method leverages domain engineering knowledge in the design and construction of staircase structures within the built environment to separate inclined staircase points within the point cloud and subsequently design a library of parametric staircase instances. In this context, the principles used in the design of parametric staircase instances are based on standard considerations in most of the investigated staircase instances. Specifically, the design of parametric staircase instances assumes regularity within each stair flight, such as consistent step height, width, and depth. While this assumption holds for many common staircase types, it may not be valid for non-standard or architecturally unique designs, potentially limiting the generalization of the method. As mentioned in Section 3.1, staircase structures can be designed according to both utilitarian and architectural functions, and their geometric design and inherent properties can differ from these standards. Therefore, the proposed method, and specifically the designed parametric models, can only be implemented for building projects that adhere to standard design.

The evaluation of the proposed approach has been conducted on eight publicly available datasets, each representing different staircase geometries, configurations, and design complexities. These datasets encompass a diverse set of examples, including varying numbers of landings, irregular forms, and occlusion levels. However, they primarily reflect real-world staircases that adhere to standard construction principles. While the method has demonstrated robust performance across these cases, further evaluation under more challenging and non-standard conditions is essential to fully understand its limitations and generalizability.

The proposed method cannot be effectively evaluated on staircases constructed from fully transparent materials, such as glass. Due to the inherent limitations of laser scanners in capturing transparent surfaces, such structures typically produce incomplete or noisy point cloud data, posing a significant challenge for accurate digital model creation.

Furthermore, the proposed method for separating staircase points can only segment points corresponding to step surfaces. This hampers the ability to create a digital staircase model with a high level of detail as it neglects other components such as handrails, outer stringers, and etc.

Also, as mentioned in Section 5.3, the proposed method still has limitations in accurately segmenting staircases with two or more landing treads and in connecting stair flows. Addressing this limitation will require the development of novel approaches for separating inclined staircase points and landing tread planes.

6. CONCLUSION

This paper presented a novel hybrid bottom-up and top-down approach for the automatic creation of digital staircase models with different configuration designs from dense laser scan point clouds.

In contrast to conventional data-driven approaches that rely on traditional point cloud processing methods, the proposed method leverages domain engineering knowledge in the design of staircase structures to separate inclined staircase points. It also integrates this knowledge with the advantage of parametric modeling to consider semantic relationships between components and formulate their interactions. This improves the geometric consistency of the digital model and helps overcome prevalent obstacles and challenges, such as noise and clutter, during model fitting and in estimating the optimal values for element parameters.

The test results on eight distinct staircase instances with different configurations and geometric designs demonstrate that the proposed approach can automatically generate parameterized digital staircase models with a mean absolute error of 5 cm in estimating model parameters. This can enrich the level of development and level of detail in existing digital building models and provide further processing possibilities for improved decision-making for facility management tasks, redesign and etc.

Despite careful consideration and promising results, the proposed method cannot model all components attached to staircase instances. Additionally, the method faces challenges with staircase instances constructed using glass and mirror materials since laser scanner beams do not accurately reflect off these surfaces, thus generating clutter and noise. This, in turn, poses difficulties in calculating geometric features and subsequent staircase point separation steps.

Further research should look into improving the accuracy of separating staircase components by testing novel approaches, such as AI semantic segmentation models, and enhancing the level of detail in the reconstructed digital staircase model by modeling other components, such as handrails, outer stringers, and similar elements.

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AVAILABILITY OF THE DATA

The point cloud data used in this research are publicly available through the links below:

Data from the Technical University of Munich: https://doi.org/10.14459/2024mp1742891

Data from the Oregon State University: https://oregonstate.app.box.com/s/gwny1xfxezpgo02sv2jt0hc6pwfpgg7s

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