Automatic creation of digital building twins with rich semantics from dense RGB point clouds through semantic segmentation and model fitting

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Abstract. Digital twins have emerged as a crucial tool for the operation and maintenance of buildings and infrastructure. A digital twin (DT) is a virtual replica of assets that provides valuable insights into real-time simulation, and monitoring. In this regard, laser scanners have become a critical component in the creation of DTs for built environments, owing to their ability to capture highly accurate point clouds of scenes. This paper presents an automatic algorithm for the creation of digital building twins with rich semantics and coherent geometry from the dense RGB point cloud. The proposed method aligns the capabilities of artificial intelligence (AI) methods in scene understanding with domain knowledge to overcome the data challenges. The results demonstrate the effectiveness of the proposed method to generate building DT models automatically with a mean error below 6 cm between the model's parameters reported by the facilities department and the parameters of generated models.

1. Introduction

The creation of DTs denoted as Digital Twining, is an important technology that aims at providing a comprehensive digital replica of built facilities for inspection, planning, management, and control processes. Recently, significant progress has been made in developing sensors and reality-capturing techniques (León et al. 2019). Laser scanner technology provides an accurate and efficient way to capture and analyze building data, aiming to improve building performance and sustainability (Volk 2014). Building digital twinning using laser scanner point cloud datasets involves the creation of a virtual replica of a building's physical assets using data collected from the indoor and exterior spaces. Despite the potential advantages of high-density point cloud collection at elevated speeds and precision, the process of scanning large-scale buildings has been consistently associated with challenges such as complex space layouts, clutter, and obstructions (Ochmann et al. 2015). Resulting raw data such as images and point clouds require substantial processing to obtain a high-end geometric-semantic model (i.e. a building information modeling (BIM) model) that is suitable for engineering purposes. This paper contributes a comprehensive workflow addressing this requirement and facilitates the creation of accurate, topologically coherent digital models with rich semantics.

2. Related work

Over the last decade, a significant number of studies have explored various aspects of creating DT models of buildings under the term "Scan to BIM", in which authors process remote sensing data for creating DTs. These include data acquisition, processing, and modeling techniques (Bosché et al. 2015, Laing et al. 2015, Corso et al. 2019, Lu and Brilakis 2019, Agapaki and Brilakis 2022). Xiong et al (Xiong et al. 2013) developed an automatic 3D reconstruction framework that used the voxelized point cloud to recognize the patches such as walls, ceilings, or floors based on boundary limits. Ochmann et al. (Ochmann et al., 2015) developed an automatic data-driven approach for reconstructing parametric 3D models of the indoor environment, such as the floor, ceiling, and wall using volumetric 3D solid shapes. To improve their previous works, Ochmann et al. (Ochmann et al. 2019) proposed a novel method for reconstructing parametric, volumetric, and multi-story building models. They define the modeling task as an integer linear optimization problem. Nikoohemat et al. (Nikoohemat et al. 2020) used the combination of geometrical features of planar surfaces and their topological relation (e.g., distances and parallelism) to reconstruct the geometric and semantics of indoor volumetric models. Tran and Khoshelham (Tran and Khoshelham 2020) presented a combination method consisting of shape grammar and a data-driven approach that uses a reversible jump Markov Chain Monte Carlo (rjMCMC) algorithm to guide the automated application of grammar rules in the derivation of a 3D indoor model.

Despite all progress, the automatic creation of the building's DT has always been associated with the limitations such as; large-scale data processing (Wang and Kim 2019), presenting coherent volumetric and semantic 3D models (Boje et al. 2020), and understanding topological relationships between elements (Xue et al. 2019), which creates several challenges in terms of automation and level of details (LOD). In most developed algorithms, significant assumptions (e.g. equality of height and thickness of walls) and thresholds *th* (e.g. angle and distance to find the location of common walls shared between spaces) and requirements (e.g. the location of sensors or spaces seed points) have been considered that prevent the creation of a consistent model and can only be implemented for a limited range of buildings with a specific layout and design (Bassier and Vergauwen 2020). In this paper, we aim to use the capabilities of AI methods along with the existing knowledge in the design and construction of buildings to develop a powerful tool to meet the challenges in this field. Our goal is parametric modeling of a wide range of buildings, each with a unique layout and design.

3. Proposed method

We propose an automatic pipeline for creating DT models of the building's structure using the dense RGB point cloud (Figure 1). The proposed method aligns the domain knowledge with AI capabilities to increase accuracy and efficiency. To overcome existing limitations, we use human knowledge of building structures and their components' functional relationships to make them available for computational processing. We take advantage of the top-down approach by fitting a highly parametrized building model with sufficient degrees of freedom to the observed data. The details of the steps are given in the following subsections.

3.1 Semantic segmentation of point cloud

The proposed method involves a crucial initial step of performing semantic segmentation of the indoor point cloud and separating the main elements that comprise the building's structure. Ceilings and walls are major elements of any building and play crucial roles in determining the spatial layout and design. Over the past decade, the proliferation of deep learning concepts has revolutionized the field of computer vision and had a profound impact on construction society. With advancements in technology, researchers have been able to leverage the unique capabilities of AI methods to perform semantic segmentation of large-scale point cloud datasets. Specifically, our proposed workflow focuses on using AI methods to extract wall, ceiling and floor elements in complex and cluttered indoor environments, which has traditionally been a challenging task for conventional methods.

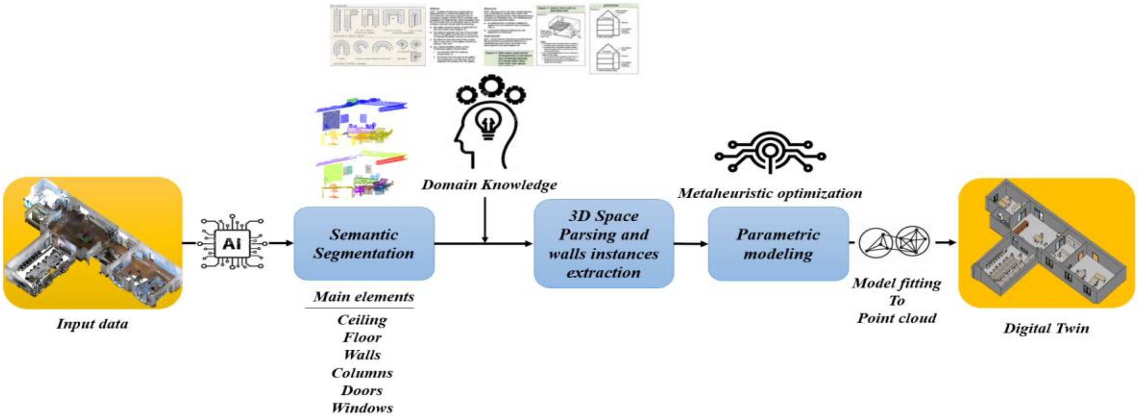


Figure 1. The proposed workflow for the creation of the DT model of the building structure.

In this study, we employ a pre-trained semantic segmentation model based on the point transformer network (Zhao et al. 2021) (Figure 2). The point transformer network is a novel and efficient semantic segmentation network, which uses the self-attention layer with a combination of simple linear layers and Multi-Layer Perceptron (MLP). The point transformer layer is invariant to permutation and cardinality and is thus inherently suited to point cloud processing. The primary objective of this step is the detection of wall and ceiling points to partition the 3D spaces. To accomplish this, we utilize a semantic segmentation network pre-trained with the Standford 3D dataset (S3DIC) (Armeni et al. 2017). The S3DIC dataset is a well-known benchmark dataset of 3D indoor point clouds comprising thirteen object classes, including ceilings, floors, walls, and furniture.

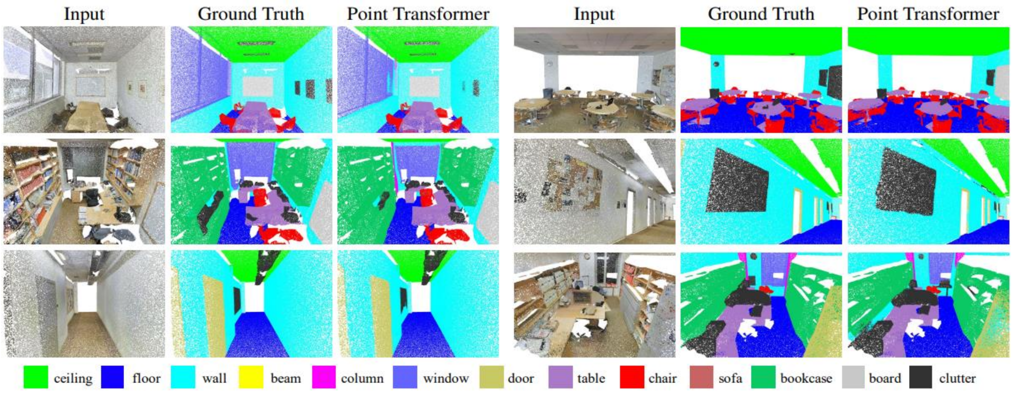
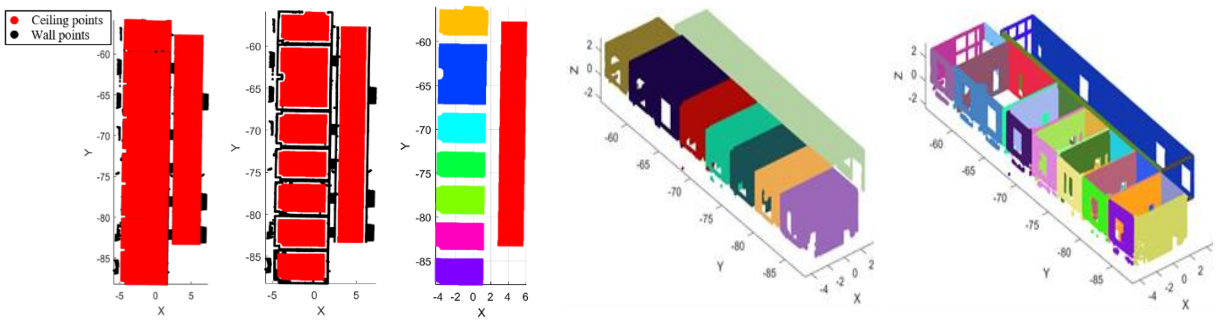


Figure 2. The semantic segmentation results on the S3DIS dataset using point transformer network (Zhao et al. 2021).

3.2 3D space parsing and walls instances extraction

For creating a high-quality digital twin of existing buildings, individual rooms and spaces are the basic building blocks and hold considerable importance in creating an accurate and detailed virtual representation of a building (Pan et al. 2023). A room or space, by definition, is a confined area within a building that possesses specific functional, and structural traits. These characteristics can encompass diverse attributes such as size, shape, ceiling height, floor type, and other distinctive features that are unique to the given space. In order to achieve a successful partitioning of 3D spaces and extracting wall instances, a knowledge-based method is employed that utilizes a hybrid top-down and bottom-up approach (Mehranfar et al. 2022) (Figure 3). The proposed method involves the analysis of wall and ceiling points at their junction to identify the central part of an individual enclosed space surrounded by walls. To accomplish this, the ceiling point in *th* distance from the wall points is removed from the ceiling segment. This results in the remaining ceiling point clouds being scattered segments that are distant from the walls. Next, the density-based clustering method (DBSCAN) (Ester et al. 1996) is applied to the remaining points of the ceiling element to create unique segments. Finally, a hierarchical nearest neighbour method is employed to assign the correct cluster label to each 3D point in the point cloud space, including the ceiling, walls, floors, and furniture.

In the context of digital twinning, walls serve as critical elements that define the boundaries and spatial layout of individual rooms. Once the point cloud data has been captured, walls can be extracted using segmentation and clustering through traditional methods or AI techniques. Due to the similar geometric and spectral features between wall points and other elements in the building environment, the detection of wall points would not be without error. We combine the bottom-up knowledge-based approach to reach a high accuracy in detecting the location of walls. The ceiling and wall elements have common outer and inner boundaries within an enclosed space. By utilizing the boundary points of the ceiling, we can extract the footprint of the walls that correspond to each 3D space. When dealing with a closed space that contains several intersecting walls, changes in the principal component analysis (PCA) parameters can indicate breakpoints or abrupt changes. These abrupt changes serve as the endpoints of each wall, where the curvatures are altered. To begin, the Alpha shape (Edelsbrunner et al. 1983) and Mean Shift (Cao et al. 2019) methods are used to extract the boundary points of the ceilings. Subsequently, these points are sorted in the x-y plane using the traveling salesman problem (TSP) algorithm (Sangwan 2018). Next, the PCA coefficients are calculated for each point by considering the *k* neighbour points that are sorted. Finally, a histogram analysis is performed on the real part of the PCA coefficient values to identify the locations of abrupt changes in these values. The points that are located between two consecutive breakpoints are determined as the surface points of a wall. Finally, the points that correspond to each wall within the 3D space are extracted from the original point cloud by considering a buffer around the separated points.



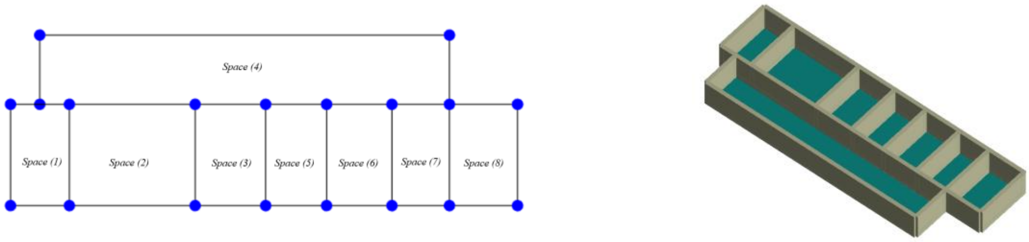
(a) (b) (c) (d) (e)

Figure 3. Overview of the proposed algorithm for 3D space parsing, (a) ceiling and walls points, (b) removing ceiling points at *th* distance from walls, and (c) clustering remaining ceiling points using the DBSCAN algorithm, (d) individual 3D spaces, (e) 3D wall instances (Mehranfar et al. 2022).

3.3 Design a highly parameterized building model

To create a DT model of a building's structure, a top-down approach is used and the task of digital geometric representation is considered as designing a highly parametrized model. Parametric modeling refers to creating a dynamic digital model that can be manipulated and simulate changes to the building's structure parameters (Sacks et al. 2004). The parametric design is based on pre-defined values and rules known as 'parameters'. In the parametric models, rules create relationships between different elements, and any change in the model is handled automatically by internal logic arguments. The difference between the building's layout is in the dimensions of the spaces in the 2D/3D planes which in this regard, the position of walls and slabs in building space play important roles. In this regard, the information extracted from the 3D space parsing and wall instances extraction step are used to create an initial floor plan mask.

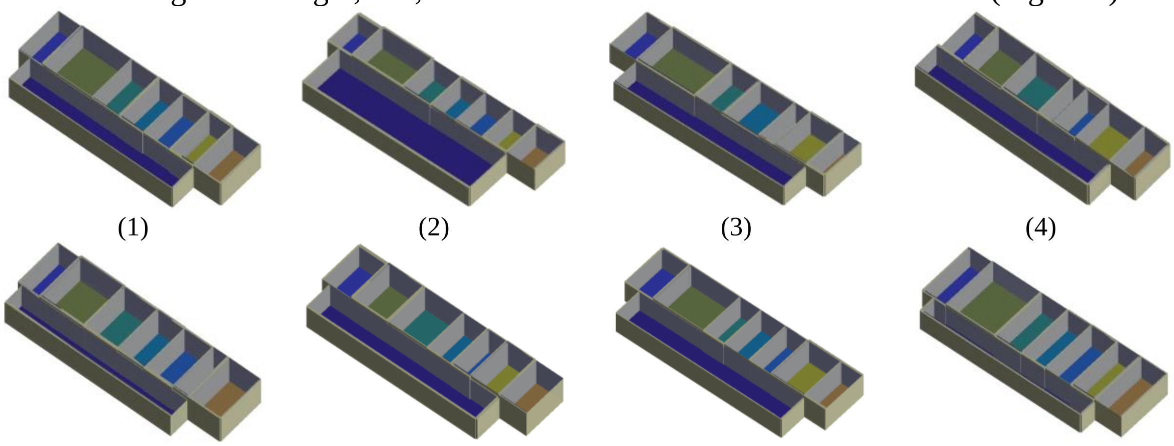
This mask is generated by a plane-plane intersection data-driven approach (Vosselman and Dijkman 2001) and represents the current layout of the building space (e.g., offices, halls, storage, etc.) (Figure 4).



(a) (b)

Figure 4. (a) Initial floor plan mask, (b) DT model extruding from floor plan mask.

After generating the initial floor plan mask, a set of geometrical/mathematical rules and constraints are considered and are applied as internal relationships between the set of walls and slabs. The logic behind these rules and constraints is the existing knowledge of building design and construction. For example, office buildings are generally designed in accordance to the "Manhattan world" assumption. Therefore, for these kinds of buildings, after the generation of the initial mask, the restriction of perpendicularity of walls and slabs is applied. The output of designing a highly parameterized building model is a DT model in which the rules and restrictions are designed and applied so that any change in the internal parameters of a wall, such as the length and height, etc., will affect other related walls and elements (Figure 5).



(1) (2) (3) (4)

(5) (6) (7) (8)

Figure 5. Designing the highly parameterized DT model of the building's structure, the process of changing the parameters.

3.4 Optimizing the parameters of building's DT model

The initial parametric model has low geometric accuracy but a consistent semantic topology. This rough model subsequently is fitted to the point cloud data using hybrid Genetic Algorithm (GA)/Nelder-Mead optimization methods (Lasheen et al. 2009) (Figure 6). The objective function of the Points-To-Model distance is considered for reconstructing accurate geometric models using point cloud data which is done by calculating the distance of points from planes of the model. The lowest value for Points-To-Model distance denotes a superior adaptation of the DT model to point cloud data, as well as greater accuracy in estimating model parameters towards their actual values. One of the main challenges in creating the building DT models is in estimating the thickness of walls. To address the problem, we inter the thickness values in the optimization problem as unknown parameters. In other words, the walls are considered as boxes with a thickness of t, length of l and the height of h and are allowed to have different values during the model fitting process. In designing and optimizing the parametric model of the buildings, the degrees of freedom is proportional to the number of walls. It includes the geometric property of the walls, including length, thickness, height, and their location in 2D space (Table 1). These unknown parameters are imported into the optimization problem as explicit and implicit mathematical equations with geometric constraints. According to the case study, the type and number of equations and unknown values in the optimization problem change.

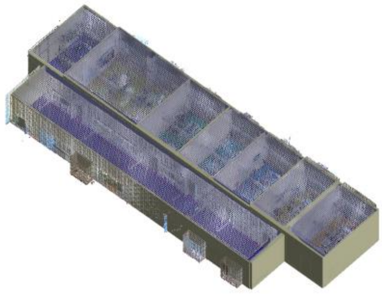


Figure 6. Fitting highly parameterized DT model to point cloud dataset using hybrid Genetic Algorithm (GA)/ Nelder-Mead optimization (Lasheen et al. 2009).

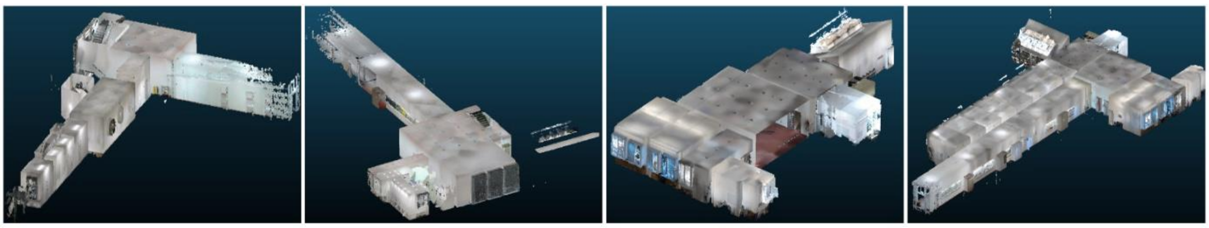
Table 1: Encoding Unknown parameters of highly parameterized DT model of the building's structure.

Building element	**Parameters**				
	X_{corner}	Y_{corner}	Length	Thickness	Height
Wall (1)	P_1	P_2	P_3	P_4	P_5
Wall (2)			P_6	P_7	P_8
Wall (3)			P_9	P_{10}	P_{11}
…			…	…	…
Building model	R_z (the parameter of rotation model around Z axis for aligning whit none Manhattan point cloud dataset)				

4. Results and discussion

4.1 Case Study

To evaluate the performance of the proposed method, four distinct indoor point cloud datasets captured from four parts of a building at the city campus of the Technical University of Munich (TUM) are considered. These datasets were acquired using a NavVis laser scanner (https://www.navvis.com). Figure 7 provides a comprehensive depiction of the datasets.



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

Figure 7. Overview of the TUM building datasets: a: part (1), b: part (2), c: part (3), d: part (4).

4.2 Experimental Results of point cloud semantic segmentation

As noted in Section 3.1, the pre-trained point transformer network is employed for the semantic segmentation of the indoor point cloud. Specifically, the model was trained on the S3DIC dataset, which includes Areas 1-4 and 6, and subsequently evaluated in Area 5 (Table 2). The building primarily serves educational and office purposes and comprises various enclosed 3D spaces, such as hallways, offices, and storage areas. The network training process utilizes specific parameters, which are provided in Table 3.

Table 2: Semantic segmentation results on the S3DIS dataset, evaluated on Area 5.

OA (%)	**mAcc (%)**	**mIoU (%)**	**(IOU) per class**												
			ceil.	**floor**	**wall**	**beam**	**col.**	**wind.**	**door**	**table**	**chair**	**sofa**	**Book.**	**board**	**Clut.**
90.8	76.5	70.4	94.0	98.5	86.3	0.0	38.0	63.4	74.3	89.1	82.4	74.3	80.2	76.0	59.3

Table 3: Parameters of pre-trained semantic segmentation network using point transformer model.

Parameter	value
Batch size	3
Voxel size	0.04
Max epoch	512
Learning rate	0.01
Momentum	0.9

As previously mentioned, the objective of the semantic segmentation step is to identify and extract the main structural elements of the building, such as ceilings, floors, and walls. This is accomplished by applying the pre-trained model to the four case study datasets. In order to assess the effectiveness of the semantic segmentation process, the manually annotated ground truth datasets are compared with the segmented point clouds. The evaluation is conducted using the Intersection-Over-Union (IOU) metric for the aforementioned classes and the average class accuracy (mAcc), and overall accuracy (OA) are presented in Table 4.

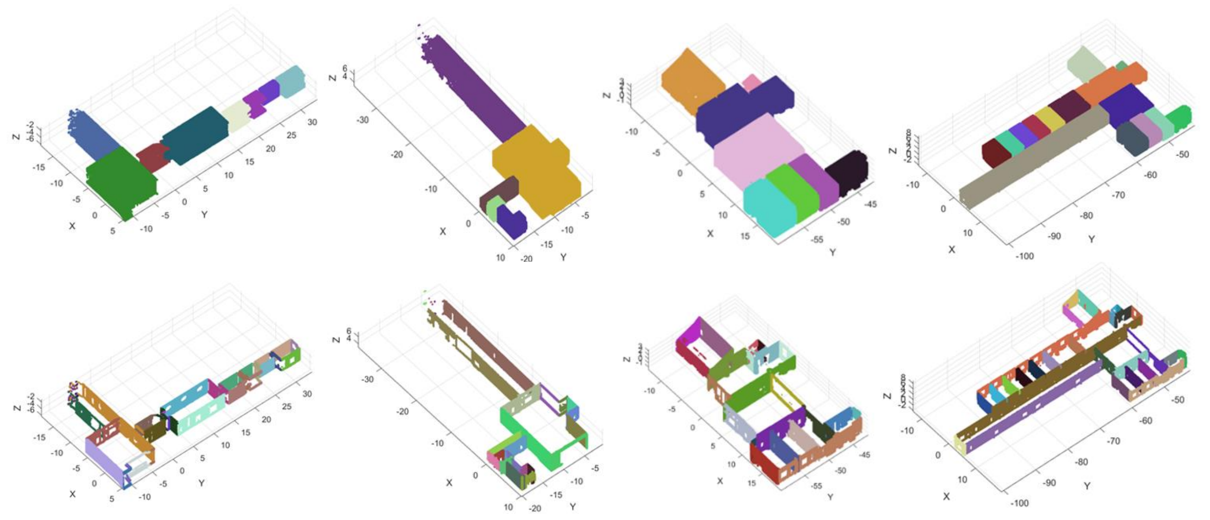
Table 4: Quantitative results of the semantic segmentation datasets using point transformer network.

TUM Dataset	(IOU) per class			mIoU (%)
	Ceiling	Floor	Wall	
Part (1)	89.17	94.53	81.78	88.49
Part (2)	85.23	92.67	83.51	87.13
Part (3)	93.58	96.64	85.72	91.98
Part (4)	91.34	94.52	83.92	89.92
mIoU (%)	89.83	94.59	83.73	89.38

The average IOU of about 89.38% is indicative of the efficiency of the semantic segmentation model in detecting ceiling, floor, and wall elements. According to Table 4, the accuracy in detecting walls was found to be lower than that of other elements, such as ceilings and floors. This discrepancy may be attributed to various factors, including the complexity of the scene, the similarity of geometric and spectral features and the utilization of different materials in building design, such as wood and glass. These factors are often inherent in building environments, and addressing this issue requires the preparation of extensive and diverse datasets to achieve optimal performance in training the semantic segmentation network. However, collecting such data for buildings with cluttered scenes is challenging and expensive, thereby imposing constraints on all developed models. Therefore, the importance of leveraging existing knowledge regarding building design and element interaction for feature extraction and modelling tasks is once again emphasized.

4.3 Experimental Results 3D space parsing and wall instances extraction

In order to partition 3D spaces in indoor environments, an initial step involves the removal of ceiling points located at a distance of 40 cm from the wall element. The selection of 40 cm as the threshold distance is informed by the typical thickness of interior-exterior walls used in office building construction, which may involve materials such as concrete or stone slabs. Subsequently, the DBSCAN clustering technique is employed in conjunction with the nearest neighbor algorithm to group points in the 3D space into distinct clusters (Figure 8). Following the separation of 3D spaces, the boundary points of the ceiling are extracted and subsequently ordered in the X-Y plane utilizing the TSP algorithm. PCA coefficients are then calculated for each point by analyzing the 50 nearest neighbor points. The location of wall footprints in each space instance are subsequently detected through the identification of abrupt changes within the histogram of the real component of the corresponding PCA coefficients. Ultimately, to extract the corresponding wall points within XYZ space, a buffer of 5 cm is employed around the footprints, and the inlier points are extracted from the original point cloud.

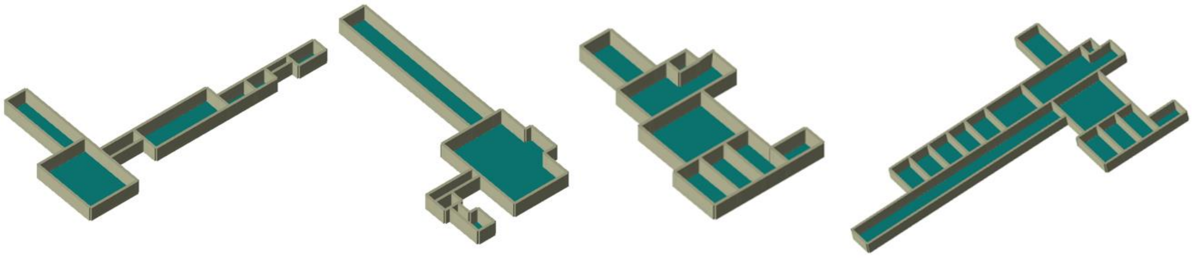


(a) (b) (c) (d)

Figure 8. The results of 3D space parsing and wall instances extraction of TUM building datasets: a: part (1), b: part (2), c: part (3), d: part (4); top: 3D partitioned spaces, and bottom: 3D wall instances.

4.4 Experimental Results Creation highly parameterized building model

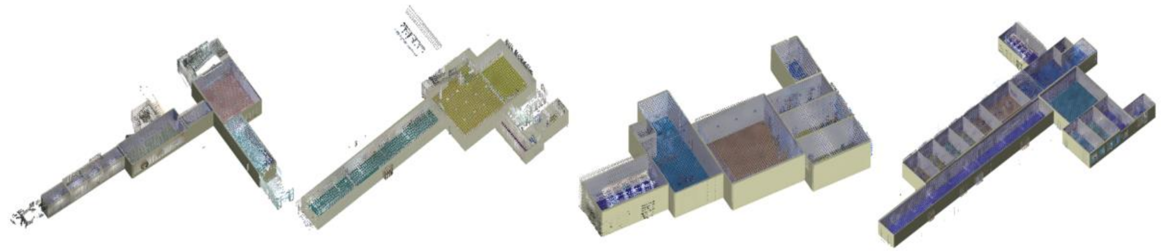
After extracting information related to 3D spaces and wall instances, the initial floor plan mask of building layouts is generated using the plane- plane intersection data-driven method. However, the indoor 3D reconstruction and generating floor plan layouts using the point cloud dataset presents a significant challenge, particularly in locating the common walls shared between spaces. Unlike other approaches that rely on distance and angle thresholds, our method employs the PCA technique to analyze the 50 neighbors surrounding each query wall point and group them based on direction and adjacency. Subsequently, the initial floor plan mask is extended into 3D space and subjected to geometrical and mathematical rules and constraints, including the requirement for perpendicularity between elements such as walls, slabs, and ceilings (Figure 9). These constraints serve as a basis for designing the parametric models, as described in Section 3.3. Finally, the highly parameterized building models are fitted to the point cloud through the optimization process and the best value for the parameters of the building model is extracted (Figure 10).



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

Figure 9. The highly parametrized DT model of TUM building datasets: a: part (1), b: part (2), c: part (3), d: part (4).

Table 5 presents the convergence (loss) values obtained during the process of optimizing building DT model parameters. Also, the results of the creation of the DT models are evaluated based on the model parameters information (e.g. height, length and thickness of walls) reported by the facilities department and the generated models. Our evaluation reveals overall mean errors of approximately 0.04 m, 0.08 m, and 0.05 m for estimating the height, length, and thickness of walls, respectively. These findings suggest that the proposed method is capable of creating high-quality DT models of the indoor environment.



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

Figure 10. The process of fitting highly parameterized DT model to the point cloud: a: part (1), b: part (2), c: part (3), d: part (4).

Table 5: Quantitative results of the building DT creation.

TUM Dataset	Model-to-points distance (m)	∆ parameters reported by the facilities department and reconstructed model (m)		
		δ_{Height}	δ_{Length}	$\delta_{Thickness}$
Part (1)	0.049	0.034	0.094	0.045
Part (2)	0.053	0.026	0.083	0.052
Part (3)	0.038	0.063	0.069	0.046
Part (4)	0.047	0.051	0.077	0.072
Overall	0.046	0.043	0.080	0.053

5. Conclusion

The proposed method is a novel framework for automatically creating building DT models. Unlike purely data-driven approaches, our proposed approach aligns the capabilities of AI methods in scene understanding along with the existing knowledge in the design and construction of building to create high-quality BIM models with correct semantics and proper relationships between components. Thanks to applying the parametric modelling process, we are able to consider semantic relationships between components which allows to overcome obstructions. Due to the mean accuracy of about 0.058 m for estimating modeling parameters, the proposed approach can promise significant progress in the field of "Scan-to-BIM" that ultimately will provide high quality DTs with high geometric accuracy and rich semantics.

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