2022 European Conference on Computing in Construction
Ixia, Rhodes, Greece
July 24-26, 2022

# SCALEBIM: INTRODUCING A SCALABLE MODULAR FRAMEWORK TO TRANSFER POINT CLOUDS INTO SEMANTICALLY RICH BUILDING INFORMATION MODELS

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## Abstract

Current approaches for the automated acquisition of Building Information Models (BIMs) of existing buildings are limited to only few elements of the building. Furthermore, most work is also related to the reconstruction of indoor elements, and is not dedicated to structural elements (e. g. walls, slabs, beams, columns, openings).
In this work, a framework for scan to BIM automation is proposed that focusses on structural elements and has a modular structure that allows the adaptation to other types of elements or types of structures. To achieve this, advanced methods for segmentation and data exploitation are being applied.

## Introduction

### Motivation

In Germany, about 70 % of the construction volume is performed in existing buildings or structures (Gornig et al., 2021). For such type of construction work, it is vital to analyse and acquire the actual state of the structure. Usually, this is performed by manual measurements and documentation, from which further information on the state of the structure can be derived.
Data acquisition techniques such as terrestrial / mobile laser scanning and photogrammetry have evolved over the past decade, including mobile mapping systems that allow efficient capturing of large spaces. The raw data is provided as an unstructured point cloud i. e., a list of point coordinates, and optionally colour and intensity values. Even though such data provides a realistic representation of the physical entity, there are no objects or semantic information in such data, from which relevant information such as measurements, areas, counts of elements or information about the condition could be derived. Additionally, unstructured point clouds are an inefficient representation of physical entities, demanding 10 to 100 times more storage capacity than semantically enriched Building Information Models (BIMs) would need. Consequently, easy-to-capture unstructured point cloud data needs to be transferred automatically into BIMs.

BIMs, being object-oriented with rich semantics, can be filtered according to elements, domains, levels, visualized, and exchanged. BIMs can be integrated into common state-of-the-art use cases and workflows, such as quantity take-off for cost estimations, referencing as-built data for structural redesign and calculation, clash detection with domain-specific models thus providing high efficiency gains compared to manual procedures.

### Objectives

This paper shall introduce a scalable, modular framework to transfer pointclouds into BIMs. We hereby focus on structural elements of buildings (walls, slabs, columns, etc.) and such relevant to the load-bearing capacities of the building (openings such as windows and doors, etc.). The framework shall be scalable in terms of the integration of other object classes, and adaptive towards different types of structures (bridges, tunnels, industrial facilities). BIMs will be provided in the open file format and data exchange standard Industry foundation classes - IFC (Bui, 2018).

### Related Work

The major research gaps in automation of scan to BIM modeling have been identified by Tang et al. The authors point out that among others methods (i) adaptive to other environments, (ii) robust towards occlusions and (iii) capable of modeling complex non-planar structures should be part of further research contributions (Tang et al., 2010).
All approaches introduced below are based on the processing of 3D data, because 3D data is necessary to achieve the objectives described above. It remains to be noted that other existing methods reduce the problem of reconstruction of point clouds into BIMs to a 2D task detecting the layout plan of a building (Okorn et al., 2010), or creating the 3D model from the floor plan (Turner and Zakhor, 2014). All approaches introduced in the following are based on the processing of 3D data and seek the reconstruction of 3D BIMs. The objectives of our research including scalability and adaptivity to other structures can only be achieved processing 3D data with full 3D BIM reconstruction. Whilst buildings mostly consist of horizontal and vertical surfaces in rectangular configuration, infrastructure or industrial assets involve more complex geometries that can only be reconstructed based on 3D approaches. The preliminary work relevant to our approach is introduced in the following.
Bassier et al. have proposed an approach for reconstructing walls and rooms based on heuristic reasoning that is capable of detecting rooms that are not limited to one storey and that can deal with cluttered and noisy environments, where parts of the walls are occluded from interiors. Within this approach, planes are fitted into the point cloud, fol-

lowed by the clustering and reconstruction of the individual wall segments themselves. The walls are represented as IfcWallStandardCase according to the open data exchange standard IFC version 4 (Bassier et al., 2018). This method achieves good accuracies, but covers only walls and room topology.
The method proposed by Ochmann et al. allows the reconstruction of BIMs of walls, doors, windows and ceilings through energy minimization also providing room topology as part of the reconstruction process (Ochmann et al., 2016). However, the method seems limited to the covered types of objects and not adaptive to other types of elements or buildings.
Macher et al. follow a three-step approach, performing a segmentation into subspaces (i. e. rooms), segmenting ceilings and walls per subspace followed by the 3D reconstruction of walls and slabs. Occlussions and clutter are segmented using a heuristic approach assuming that points forming a corner belong to walls and cluttering objects do not reach the ceiling (Macher et al., 2017). The method seems reasonably accurate with a stable approach to dealing with clutter. However, integrating other types of objects seems difficult since the sequence of segmentations does not allow easy alterations.
All known research has not yet provided a scalable scan to BIM framework, allowing to add other elements or to cover various types of buildings in a modular approach. Such a framework will be introduced in the following.

## Scan to BIM automation framework

### Fundamentals

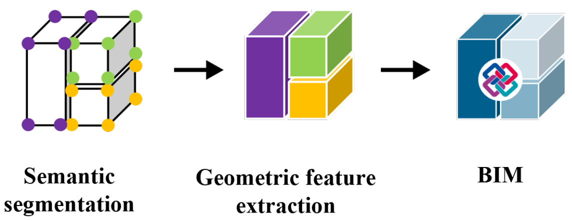


*Figure 1: Overview of Scan to BIM process steps*

To achieve scalability and full automation within scan to BIM methods, it is essential to define three separated main process steps: (i) semantic segmentation of the input point cloud, (ii) geometric feature extraction and (iii) BIM authoring, see Figure 1. Note, that there are some more process steps required for the preprocessing of the acquired data, namely 3D reconstruction, registration of terrestrial point clouds as well as filtering and cleaning. There are common software tools, e. g. Open3D (Qian-Yi Zhou et al., 2018), CloudCompare (Girardeau-Montaut, 2020) providing reconstruction, registration and filtering algorithms and tools. For this research, we assume that a registered and filtered point cloud is provided, thus the mentioned steps will not be explained any further.
Although the focus of the proposed methodology is the BIM reconstruction of structural elements (walls, slab, columns, etc.) or such affecting the structural behaviour of the building (openings, etc.), it assumes that all elements are visible and can thus be captured using common reality capturing technologies resulting in point clouds of the building. Elements covering the structural members e.g., suspended ceilings, wall coverings, facade systems, etc. need to be removed before capturing the structure. Other cases including scanning of building component interiors (concrete reinforcement, ducts, etc.) are subject to other research. However, both approaches may be combined in the future.
The proposed method also requires a certain degree of data completeness, i. e. that all structural members' visual surfaces should be captured and present in the point cloud. Exceptions are allowed for certain types of elements, where the lack of a surface in the point cloud is very common, e. g. for base slabs whose bottom surface touches the ground and top slabs that will neither be scanned from outside and indoor capturing. To manage the exceptions, knowledge-based routines are implemented.
Within the semantic segmentation, building components of the scanned structure are recognized. Every point of the point cloud is annotated with a semantic label, representing the object class such as wall, slab, column, etc. Per object class, individual objects must be clustered and the respective geometric features (dimensions, placement, orientation, shape) are extracted. Performing semantic segmentation before geometric feature extraction provides major advantages, since individual geometric feature extraction routines per object class can be implemented. Finally, all extracted information is combined into a BIM. Every process step is developed as an individual module. Thus, it is possible to develop per step modules for different types of structures (e. g. buildings, bridges, tunnels) with different requirements. In buildings, rectangular and planar objects are very common. Bridges follow the road alignment, thus forming objects swept along the alignment path with more complicated geometry compared to buildings. It is obvious, that different approaches are needed for semantic segmentation and geometric feature extraction for different types of structures. Regarding BIM modelling, specific software tools and modelling workflows are adequate per structure type.
Hence, these three steps allow for a modular development of each of them, and an easy integration of other element classes or an adaption to other types of structures. In the following, all three steps will be outlined, mostly referring to the building sector. Where applicable, approaches for other types of structures will be depicted.

### Semantic Segmentation

Recently, Machine Learning methods have proven high accuracies in semantic segmentation of pointclouds of buildings. A good overview of different approaches on the semantic segmentation of indoor point clouds of buildings is presented in the ScanNet Benchmark challenge. The ScanNet dataset consists of more than 1500 scans of indoor rooms (mostly of type bedroom / hotel and living room / lounge) with 20 semantically annotated classes, e. g. floor, wall, chair, sofa, window (Dai et al., 2017a). Hence, the candidate approaches in the ScanNet benchmark challenge can be considered a good starting point to identify suitable neural network architectures for semantic segmentation on a structural level of buildings.

From the ScanNet Benchmark Challenge, SparseConvNet (Graham et al., 2018) being one of the leading approaches was chosen to perform experiments on the semantic segmentation of point clouds. SparseConvNet provides a neural network architecture with submanifold sparse convolutions and requires excessive amounts of data for training. Whilst ScanNet provides 1513 semantically annotated indoor scenes (Dai et al., 2017a), the provided classes do not match the requirements of this work. Within the semantic segmentation challenge, ScanNet contains 20 classes e.g., basic building element classes such as walls and floors, furniture (chair, sofa, etc.) or building installation (sink, toilet, etc.) Hence, training data had to be acquired covering an adaquate class scheme of structural element classes in buildings.

Since manual annotation of training data is labour-intensive and error-prone, a method to acquire synthetic training data from BIMs using IFC (Bui, 2018) was developed.

Acquiring synthetic data from BIMs requires a two-step

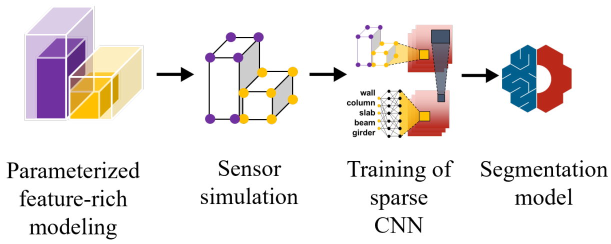


*Figure 2: Generating annotated point clouds from BIMs*

process: (i) realistic texturing of BIMs in a 3D content creation engine and (ii) a sensor simulation toolkit. As there is a close integration with IFC via IfcOpenShell (Krijnen, 2021) and BlenderBIM , Blender was chosen as a 3D content creation engine. From the sensor simulation toolkits with Blender interface or integraton, Helios++ (Winiwarter et al., 2021) and BlAInder (Reitmann et al., 2021) were examined as possible alternatives. Helios++ provides a high-performance sensor simulation framework and was used in (Noichl et al., 2021) with Blender to generate point clouds of industrial facilities. However, Helios++ lacks the feature of acquiring colour values during scanning. Colour values are crucial as they are captured by real-world laser scanners and are thus processed by the segmentation algorithms. BlAInder shows good performance and can be used with the most recent Blender versions with advanced tools for BIM interaction available from BlenderBIM and is used in the recent research.

The approach generating synthetic point clouds from

*Table 1: Colors and respective classes*

| Class name | RGB | Colour |
|---|---|---|
| Wall | 0, 0, 170 | |
| Slab | 170, 0, 0 | |
| Column | 0, 50, 0 | |
| Window | 200, 0, 100 | |

BIMs is displayed in Figure 2. The first step is to produce BIMs varying in dimension and configuration of elements e.g., overall length, number and position of windows, etc. Within the proposed approach, Autodesk Revit is applied with its visual programming interface Dynamo. These BIM models are then transferred to Blender via Industry Foundation Classes (IFC) (Bui, 2018). In Blender, textures are applied according to the specific element class using Blender's UV mapping methods. From seven scanner locations point clouds are acquired with a rotating LiDAR scanner, similar to real-world terrestrial laser scanners in terms of resolution and scanner characteristics. To acquire ground truth data, the respective class labels are inherited from the IFC classes and written to the output point cloud. The colour values and respective classes for visualization can be found in Table 1.

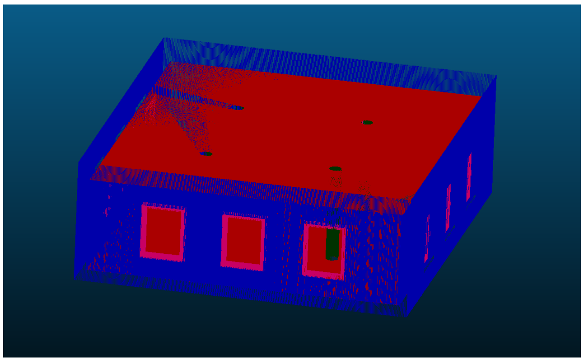

*Figure 3: Example scene with ground truth labels*

With the described workflow, a dataset of 170 scenes has been generated. One example scene is displayed in Figure 3. With the dataset, different models have been trained using sparse convolutional layers, filters, etc. from (Graham et al., 2018). Before training, data has been preprocessed including subsampling of the raw data from the sensor simulation using CloudCompare's subsampling function (Girardeau-Montaut, 2020).

With achievable accuracies of more than 90 % (mean Intersection over Union), training and inference show promising results, however a good prediction accuracy on real data could not be achieved. The key to achieving a ro-

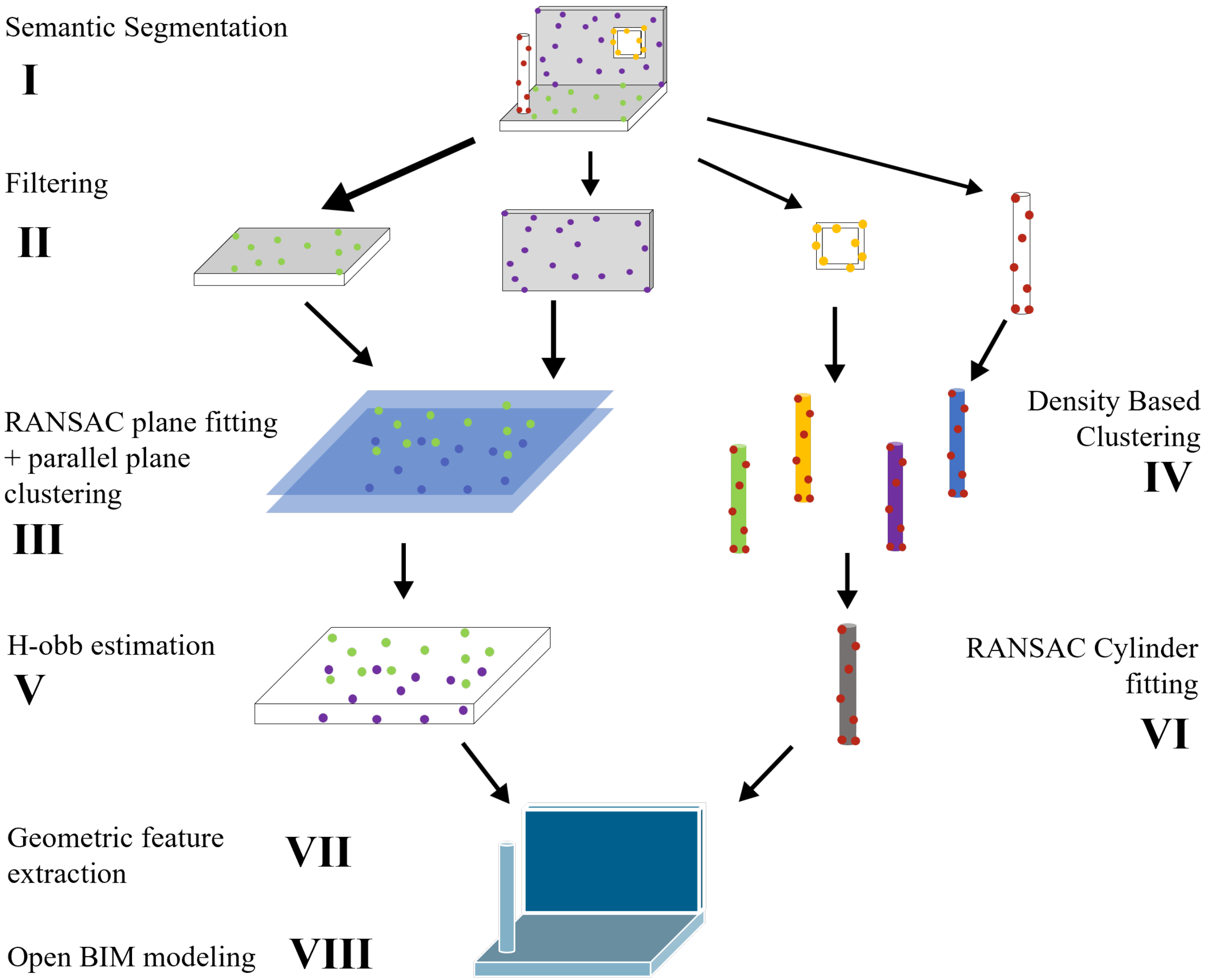


*Figure 4: Overview of the presented framework*

bust classification on real data is to enable the trained network to learn an abstract representation of the underlying features. Possible approaches to facilitate robust domain adaptation will be considered in the discussion section.

**Geometric Feature extraction**

Geometric feature extraction requires applying the appropriate segmentation tools based on a priori knowledge about the semantically segmented objects as presented in Figure 4. From semantic segmentation (Figure 4 - I), a point cloud is derived that can be filtered by the respective object classes (e.g., slab, wall, window), see Figure 4 - II. After obtaining the filtered point cloud (i.e., only points of one object class), single objects need to be clustered together. In the context of the examined building components, mainly plane fitting and parallel plane clustering (Figure 4 - III) or Density Based Clustering (Figure 4 - IV) are applicable. After clustering, the geometric features of the single element point cloud need to be extracted, which covers the dimensions, position and orientation of the object, using H-obb estimation (Figure 4 - V) or cylinder fitting (Figure 4 - VI). Geometric features and semantic object information need to be stored intermediately (Figure 4 - VII). This information can later be used to instantiate BIM objects (Figure 4 - VIII). In the following, our approach to geometric feature extraction will be explained for common elements such as walls, slabs, windows and columns related to the applied method. All process steps I to VIII are considered modules of *ScaleBIM* framework. Note, that some of the procedures can be applied to similar elements, too.

The main subdivisions of a building are its levels, usually formed by respective slabs. BIMs of buildings are also organized according to the building levels, hence levels' and respective slabs' geometric features need to be extracted primarily. As an input the estimated maximum slab thickness is needed as a threshold value to group corresponding segmented planes. Top and bottom levels, e.g. roof or base slab, are then added with an estimated slab thickness, if the top or bottom surface is not scanned. This is required since the upper surface of the top slab may be scanned, but the lower surface of the base slab will not be scanned since it is connected to the foundations and/or touching the subsoil. All detected levels will be returned as a list for BIM modeling. The elevations also provide the minimum and maximum Z values to assign elements to the building level, another essential information to ultimately provide functional BIMs.

Walls typically consist of parallel vertical surfaces. In most cases, walls are planar elements. Consequently, the first approach to extracting wall geometric features is to segment planes from the segmented wall point cloud. For plane segmentation, an efficient implementation of the Random Sample Consensus Algorithm (RANSAC) as presented in (Schnabel et al., 2007) is used in this research.

Subsequently, the corresponding surfaces forming a wall are grouped together by estimating the mean distance between two planar point clouds (Figure 4-III). If the distance is below the defined threshold, two planes are considered the two surfaces of a wall. Note, that the threshold needs to be estimated manually and defined as an input for the wall clustering function. This is being considered a feasible option since the maximum wall thickness within a building can be estimated visually or with few measurements from either the physical object or the raw point cloud of the building easily.

The next step in geometric feature extraction of walls is to obtain dimensions, location and orientation of the segmented and clustered wall point clouds. As walls consist of parallel planar surfaces, their volume can be represented as a cuboid described by extremal corner points. This is also referred to as a Bounding Box of the point cloud. Generally, axis-aligned bounding boxes describe the minimal volume of a point cloud aligned to a coordinate system. Oriented bounding boxes describe the minimum bounding volume oriented along with the point cloud. In most cases, an oriented bounding box would represent the minimum bounding cuboid for a wall point cloud. Unfortunately, the methods for obtaining a bounding box implemented in frameworks such as open3D (Qian-Yi Zhou et al., 2018) show poor accuracy for cuboidal point clouds, see Figure 5. The main reason for the poor accuracy is that these methods rely on the principal component analysis. Such methods may perform poorly on cuboidal point clouds. To overcome these issues the *horizontal aligned oriented bounding box* (h-obb) is being introduced, where the problem of estimating the minimum bounding box is reduced to a 2.5D problem.

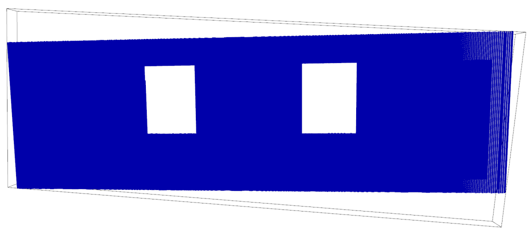

*Figure 5: Poor accuracy of oriented bounding box estimation methods based on PCA*

The main assumption for estimating the h-obb is that the lower and upper surfaces of clustered wall point clouds are horizontal. Although this seems to be a major simplification, it is comprehensive that buildings are structured in horizontal levels forming the floors of the building. While some walls may be shaped differently with sloped lower and/or upper edges, the assumption generally works for most of the walls and also matches the need of the subsequent BIM modelling, with BIMs also being structured by levels with each element assigned to its host level.

First, all points are projected onto a horizontal surface, then the 2D convex hull is computed using scipy (Virtanen et al., 2020). For every line in the convex hull, the point cloud is rotated onto the x-axis. Subsequently, the minimum and maximum coordinate values are determined. On the basis of the minimum/maximum coordinates a bounding box can then be formed. Per line of the convex hull one candidate bounding box is estimated. By comparing the volume of every candidate bounding box, the minimum bounding box can be identified i. e., the candidate bounding box with the minimum volume. For every bounding box the extremal coordinates are returned for subsequent BIM modelling.

It is obvious, that the 2.5D approach is a major simplification. However, this is acceptable if the topology of buildings is considered and leads to robust results. An example of an estimated h-obb is displayed in Figure 6, where the grey mesh represents the bounding box covering all blue coloured points of the point cloud. The minimal representation of a h-obb can be given by the green and orange (maximum/minimum) points, since h-obb have a horizontal rectangular base plane. The rectangle can be represented by only two points, if their spatial relationship is defined. Assigning the minimum z-coordinate (orange point) to the maximum point (green) results in the point pair describing the base rectangle. For convenience, all corner points in the lower horizontal plane, minimum/maximum vertical coordinates and base points (rose coloured in Figure 6) can be returned, too. H-obb estimation can be used for walls, slabs or similar elements and follows plane fitting and clustering as indicated in (Figure 4-V).

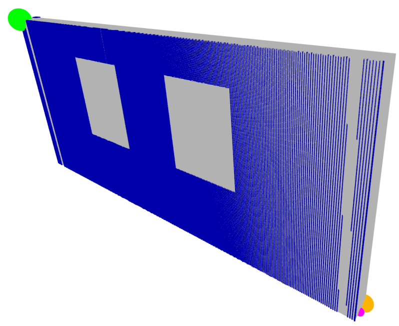

*Figure 6: h-obb of segmented and clustered wall point cloud*

Segmented windows will be displayed as a group of windows, i. e. all points assigned with the window class. Hence, single-window point clouds need to be clustered before geometric feature extraction. Typically, the number of objects per class in a point cloud segment is not known a priori. Since it does not require the number of clusters as an input, the Density-Based Clustering Algorithm (DBSCAN) as introduced in (Ester et al., 1996) is used here to identify single objects from the segmented point cloud with robust results and is applied for elements such as windows or columns as indicated in Figure 4-IV. The implementation of DBSCAN in open3d (Qian-Yi Zhou et al., 2018) allows for fluent integration into the proposed workflow.
After clustering single windows, the h-obb will be estimated per clustered object point cloud to extract geometric features.
As with the windows, single columns first need to be clustered from all points assigned with the column class using DBSCAN (Ester et al., 1996). As columns may be cuboidal as well as round, the type of column then needs to be detected. This can be achieved using curvature estimation according to (Douros and Buxton, 2002), a method implemented in CloudCompare's geometric features computation (Girardeau-Montaut, 2020). An example of curvature estimation on round and square columns is shown in Figure 7, with green-yellow points indicating round columns and grey-white sections encompassing the filtered square columns. The type of column per clustered column can be determined by filtering the curvature values with higher values representing round columns and low curvature indicating square columns.

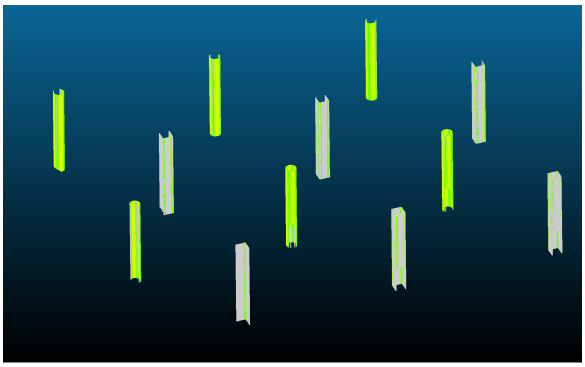

*Figure 7: Distinguishing round and square columns using curvature estimation*

Depending on the type of column the geometric features will be exploited (i) using RANSAC cylinder detection (Schnabel et al., 2007) for round columns (see Figure 4-VI) or (ii) h-obb for cuboidal shaped columns.

### Open BIM modeling

For BIMs proprietary data formats as well as open data exchange formats exist. Whilst proprietary formats typically provide more fluent integration into BIM authoring tools and allow for full modification of the objects, the possible range for data exchange is very limited, although interfaces for proprietary BIM data formats exist in some contexts. Within scan to BIM it must be expected that the generated BIMs will form the basis for further processes such as design, construction, cost and quantity estimation, facility management, etc. Thus, BIMs should be interpretable by a wide range of software tools. Consequently, IFC is used as an output data format for the reconstructed BIMs. Although Version 4 of the IFC standard is released and becomes more common, IFC Version 2x3 is used in this research. Version 2x3 is the most common version and is supported by almost every software application that allows importing BIMs. The reconstructed BIM is displayed in Figure 8, details on the procedure of IFC model generation will be explained in the following.
For every reconstructed element class, a respective IFC class exists containing specifications about the geometric and semantic representations. The shape representation of slabs, walls and columns are specified as *IfcExtrudedAreaSolid*, the respective geometric parameters are derived from the h-obb of the reconstructed objects.
For representing a window, two objects need to be added to the IFC document: (i) an opening element represented as *IfcOpeningElement* and the window itself represented as *IfcWindow*. The dimensions and localization are derived from the h-obb, with the opening dimensions extended to the vertical faces of the wall to ensure a continuous opening on both sides of the wall. The windows themselves are represented with simplified geometric representations (see Figure 8), as further details on the window frame, glazing, etc. are not derived from the geometric feature extraction.
For completeness, property sets and material properties are added to the IFC elements, although this information was not obtained automatically.

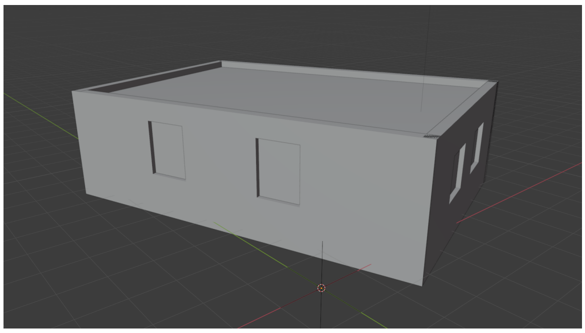

*Figure 8: Reconstructed BIM*

## Discussion

Within this research, extensive studies seeking a method for semantic segmentation of point clouds are conducted using synthetic training data, acquired from the proposed

BIM generation and sensor simulation process. However, a sufficient classification accuracy on real-world data could not be achieved so far. The reason for this is that features in point clouds of actual buildings show more variations, e. g. regarding textures, surface roughness, evenness, presence of objects, configuration of objects, layout, completeness, clutter, etc. It seems barely feasible to achieve such variations in synthetic training data.

When applying synthetic training data in Machine Learning, the problem of *Domain adaption* is widely examined and researched. Promising approaches for realistic data generation are provided using Generative Adversarial Networks (GANs). Implementations of GANs to generate high-fidelity images (Brock et al., 2019), and for small-scale point cloud completion tasks (Wang et al., 2020; Wen et al., 2021), as well as large-scale point cloud completion tasks (Dai et al., 2017b) show promising results. Katrolia et al. have provided a framework for depth domain adaptation for in-car scenes using synthetic depth images and real-world depth images (Katrolia et al., 2021).

Besides, knowledge-based approaches to semantic segmentation may even outperform machine learning approaches. Ponciano et al. have proposed a knowledge-based approach to semantic segmentation of street scenes, that achieved a F1 score of 78 % on the tested data, considerably outperforming the tested Deep Learning approach that resulted in an accuracy of 66 % (Ponciano et al., 2021).

The proposed approach to geometric feature extraction and open BIM modelling shows robustness and good performance on the tested data so far. However, error handling procedures need to be developed and implemented to deal with unforseen situations. Possible misinterpretations may occur when encountering non-typical shapes of elements such as curved walls, ramps, tilted structures, etc.

Besides error handling, the methodology needs to be developed further to cover more element classes, such as roof, stairs, installations, etc.

## Conclusions

Within the presented work, a modular scan to BIM framework, called *ScaleBIM*, with distinct steps for semantic segmentation, geometric feature extraction and open BIM modelling is proposed.

In future work, the task of semantic segmentation will be examined further. The application of machine learning on classification tasks in other domains proves that the achievable accuracies and reliability are very high. This might be the case for point cloud segmentation if domain adaptation frameworks exist on a large scale for unstructured 3D data. Besides domain adaptation approaches, knowledge-based approaches to semantic segmentation of point clouds seem currently very promising. It is cruical to take into account, that knowledge based approaches can be more computationally efficient since computationally expensive processes during the training of neural networks do not have to be performed.

The proposed methodology will also be advanced to cover other types of structures such as bridges. The challenge lies in different topologies: while buildings are hierarchically organized in levels, bridges are organized along their alignment formed by a 3D curve and respective positions on the alignment. Besides semantic segmentation, this requires different approaches to geometric reconstruction and open BIM modelling.

## Acknowledgments

This research was funded by the ERDF (European Regional Development Fund) and the german federal state of Rhineland Palatinate in the research programme *Inno-Prom*. The research was co-funded and accompanied by the construction enterprise P.A. Budau GmbH `https://www.budau.com/` situated in Idar-Oberstein, Rhineland Palatinate, Germany.

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