

BSS-Indoor: Volumetric wall reconstruction using Building Section Skeleton

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Abstract. Building Information Modeling (BIM) has become well recognized and increasingly mandated in the building sector, where Scan-to-BIM automation shows great potential for BIM users. For the ‘last mile’ or ‘last step’ of automatic Scan-to-BIM, parametric reconstruction, existing methods focus on surface reconstruction. However, BIM practitioners have to handle architectural elements as volumetric instances rather than connected surfaces. This paper proposes a volumetric reconstruction method called BSS-Indoor. The method is based on a novel Building Section Skeleton (BSS) theory which pairs the parallel and symmetric facades of the building exterior. By adapting BSS from building exteriors to interiors, BSS-Indoor reconstructs internal walls as BSS segments. Our method simultaneously locates walls and estimates their thicknesses, addressing common issues in existing solutions, such as fragmented long walls and merged adjacent walls. Preliminary experiments on a subset of the CV4AEC (3D) dataset demonstrate the effectiveness and potential of BSS-Indoor in reconstructing volumetric walls.

Keywords: Scan-to-BIM; Volumetric wall reconstruction; Point cloud processing

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1 Introduction

The Building Information Modeling (BIM) has become significantly important throughout a building's entire lifespan, covering all phases from initial design to eventual demolition [1]. To streamline the building sector with BIM, automating the creation of BIMs is extremely crucial [2]. Scan-to-BIM, a popular task that converts 3D scans captured by laser scanners or photogrammetry, shows great potential in the creation and uses of as-is BIM [3]. A typical Scan-to-BIM workflow involves four steps: scanning, scan registration, semantic segmentation, and parametric reconstruction. In recent years, solutions and datasets for registration and semantic segmentation of building interiors have rapidly evolving, which significantly boosted the Scan-to-BIM popularity [4]. However, the parametric reconstruction, which is the 'last mile' or 'last step' of the Scan-to-BIM pipeline, does not yet fulfill the actual requirements of BIM practitioners in the industry [5].

Existing methods for reconstructing building interiors focus on surface reconstruction instead of volumetric modeling. These methods reconstruct the surfaces of architectural elements, i.e., walls, floors, and ceilings, into lightweight meshes [6, 7]. Simultaneously, rooms and their closed boundaries are extracted [8, 9]. The resulting surface models or floorplans satisfy the requirements of indoor navigation [10] and fit the native geometric representation of CityGML for City Information Modeling [6]. However, BIM practitioners in the building sector pay more attention on the individual instances of architectural elements [5]. Walls and slabs are preferably modeled as volumetric instances enriched with joints and details inside the surfaces rather than separated facets that bound different rooms.

Volumetric reconstruction of architectural elements essentially involves locating the volume, outlines the volumetric shape and/or estimates the dimensions of the identified volume. For walls and slabs, thickness should be estimated. Meanwhile, walls are usually simplified as cuboids. Volumetric walls can be reconstructed by clustering the wall points produced by semantic segmentation and then estimating the bounding box of each cluster [4]. To achieve a higher reconstruction fitness to the scans, optimization models were formulated to finetune the locations and dimensions of wall boxes [11]. Moreover, wall thickness can also be predicted by deep learning after projected the point clouds onto horizontal planes [5]. However, as the height information is missing after the projection, the method reconstructs floorplans only. A common aspect among these solutions is that they separate the volume localization and dimension estimation processes. As a result, long walls are prone to being cut into pieces and adjacent walls with different dimensions are prone to being merged into one wall.

In this paper, we propose a volumetric reconstruction method for walls based on the Building Section Skeleton (BSS) [12]. Our method aims to locate and estimate the thickness of walls simultaneously. BSS is a shape skeleton defined to adapt the morphological characteristics of building exterior boundaries. Each BSS segment corresponds to a pair of parallel vertical planes representing facades or a pair of symmetric incline planes representing roofs. A BSS segment is parameterized with the radius and forms a polyhedron, which is a similar concept of volume thickness. This study transfers the BSS for building exteriors to interiors. Each internal walls are reconstructed as a BSS segment, while the external walls are detected as the parallel facades that bound buildings. Preliminary experiments on the a subset of the CV4AEC (3D) dataset [13] show that our method, named BSS-Indoor, can effectively reconstruct the volumetric walls.

The remainder of this paper will introduce our method BSS-Indoor, report preliminary results, as well as discuss the strengths and future improvement of BSS-Indoor.

2 Preliminaries: Building Section Skeleton for wall reconstruction

The fundamental concept of the Building Section Skeleton is to capture the parallel and symmetric planes of buildings, building on the classical concept, shape skeleton, in computer graphics. The identified parallel and symmetric planes can be assembled into 3D volumes which represent the space inside buildings, providing semantic information. These 3D volumes may correspond to the empty space of building interiors designated for specific functions, such as offices and corridors, or they could also be physical structures, such as walls.

BSS are defined at three levels, i.e., atoms, segments, and the relations between segments. A BSS atom is the center of the sphere inscribed by symmetric points on the exterior or interior surfaces of buildings. If the surfaces are vertical, the radius of the sphere and the normals of the inscribed points are attributes of a BSS atom. If the surfaces are not vertical, the intersection height of the two inscribed directions and the normals of inscribed points serve as the parameters of a BSS atom. When two points lie on a pair of parallel planes, then the corresponding BSS atom is equivalent to the midpoint of these two points. At the second level in the definition of BSS, a segment is a group of BSS atoms distributed on a same plane, forming a region, and sharing same radius or intersection height and normal. Hence, a BSS segment represents the medial plane of a pair of parallel or symmetric planar regions. Furthermore, by sweeping the medial vertical region of a BSS segment, there is a corresponding volume of a BSS segment, which represents the empty or physical space of buildings. The relations of BSS segments, which constitute the third level of the BSS definition, refer to their topological relations, including intersections and adjacency. For more details on BSS, please refer to [12].

In the practice application of BSS in Scan-to-BIM, there are two specific designs for wall reconstruction. Although a BSS segment could be the medial planar region of both vertical and incline planes which could be parallel and non-parallel, respectively, the planes involved in wall reconstruction are usually parallel. Therefore, we solely use BSS for vertical and parallel planes. Moreover, different mechanisms are employed reconstructing interior and exterior walls. As a BSS segment represents the medial plane of a pair of parallel or symmetric planes, the use of BSS assumes the presence of dual planes to bound a space. However, the scanned point clouds for BIM reconstruction may not always include the facades of buildings, leaving only one single plane for an exterior wall. To reconstruct both interior and exterior walls, our method captures dual wall surfaces as close as possible to each other for reconstructing BSS segments for interior walls, and as far apart as possible for reconstructing the interior spaces of buildings. Subsequently, we use the boundaries of the interior spaces to supplement the exterior walls.

3 Method

3.1 Overview

Fig. 1 shows an overview of our method. BSS-Indoor takes the segmented point clouds of architectural elements as inputs and outputs the volumetric walls. Plane detection is performed first to group points as planar primitives. Then, the method clusters the primitives in terms of their normals. In the case shown in Fig. 1, two orthogonal orientations are clustered. After that, two stages, one for proposing, the other for refining, are implemented to reconstruct the walls of each orientations.

Stage 1 locates the possible walls and outlines their vertical planar boundaries as the initial BSS segments. This stage pairs the parallel planar primitives of each orientation whose distances between each other are close or far apart enough in terms of given thresholds. After pairing, the proposed method

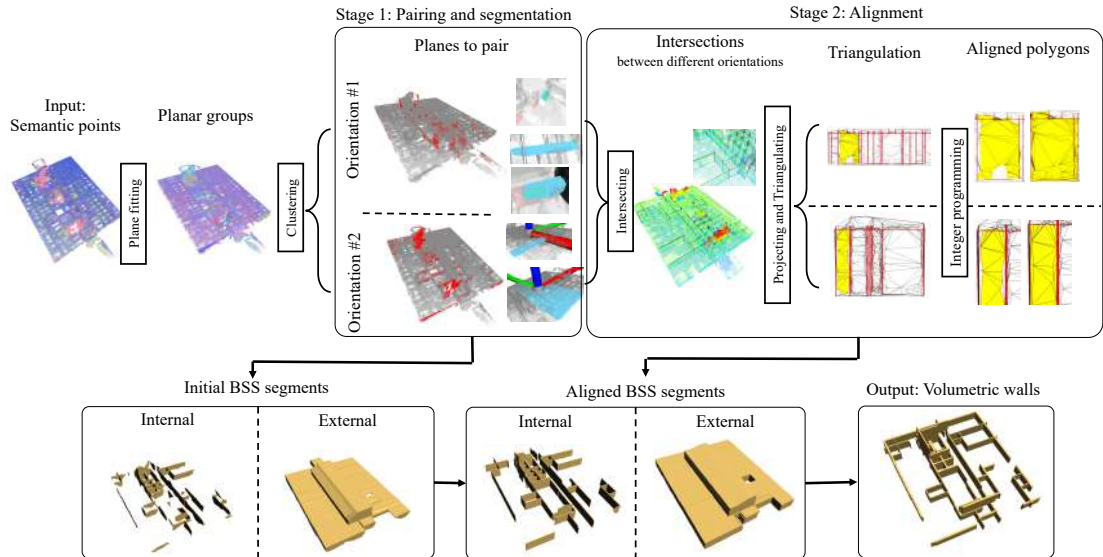


Figure 1: Overview of BSS-Indoor.

100 segments the common regions coarsely of each paired regions in an ascending order for close ones and
 101 descending order for far away ones. Note that the common region is the vertical medial region of the
 102 paired planes. However, as shown in Fig.1, the initial BSS segments have irregular boundaries. There
 103 are also topological errors including intersections and gaps between different BSS segments.

104 Therefore, Stage 2 further refines the BSS segments by aligning the BSS segments of different orientations
 105 to smooth the boundaries and remove the intersections and gaps. The aligning procedure projects
 106 the vertical regions of a BSS segment onto a vertical plane. The method then triangulates the projected
 107 extent. Triangles in the extent are labeled as inside or outside the BSS segment. Refining the boundary
 108 of a BSS segments now can be conducted by flipping the inside/outside labels of the triangles. An integer
 109 programming model is formulated to optimize the flipping for a smooth and topologically correct
 110 boundary of each BSS segment.

111 After the two stages, internal walls are reconstructed from the BSS segments formed by close paired
 112 planes, while external walls are from BSS segments composed by far apart parallel planes. The method
 113 extrudes the vertical region of a BSS segment horizontally by the radius of a BSS segment for interior
 114 walls or a standard thickness for exterior walls.

115 3.2 Stage 1: Pairing and Segmentation

116 In Stage 1, parallel planes within each cluster are paired, and the common regions of the paired planes
 117 are segmented for each orientation individually.

118 Planes within a cluster that are either closer or farther than given thresholds are filtered as potential
 119 pairs. Then, the method sorts the pairs with small distances in an ascending order for reconstructing interior
 120 walls, while pairs with large distances in descending order for exterior walls. The segmentation of the
 121 common regions for interior and exterior walls are performed individually according to their respective
 122 orders. Although a plane can be paired with multiple planes, a region of the plane can only be segmented
 123 once and paired with one of its pairing candidates. Therefore, within a single orientation cluster, BSS
 124 segments and their corresponding volumes cannot intersect with each other. By design, paired planes

125 with closer distances are segmented first for interior walls; whereas farther paired planes are prioritized
126 for exterior walls.

127 The segmentation of common regions are based on the Boolean operations of polygons. Our method
128 projects the points of each plane onto a vertical plane and then polygonizes the projected regions by
129 calculating their 2D Alpha shapes. When segmenting the common region for a pair of planes (A, B) , the
130 two polygons of each plane are separated into three parts: $A \cap B$, $A \setminus B$, and $B \setminus A$. The region of $A \cap B$
131 is segmented out as one of the initial BSS segment. The regions of $A \setminus B$ and $B \setminus A$ are retained for the
132 subsequent segmentation with the remaining paired planes of A and B , respectively.

133 After segmenting the region of a BSS segment, our method extrudes the vertical region of a BSS
134 segment horizontally in both orientations by its radius to form a 3D polyhedron, representing the initial
135 interior walls and indoor spaces (presented in the two sub-figures on the left-hand side in the second row
136 in Fig. 1).

137 **3.3 Stage 2: Alignment**

138 Stage 2 refines the initial BSS segments by aligning those of different orientations. This process includes
139 smoothing the boundaries of the BSS segments and eliminating intersections and gaps between them.

140 The alignment procedure relies on the intersections of BSS segments from various orientations. The
141 method first intersects the medial planes of the initial BSS segments, filtering out intersection lines that
142 are too distant from the segmented regions. Next, for each orientation cluster, our method projects all
143 the segmented common regions from Stage 1, along with the intersection lines, onto the vertical plane
144 orthogonal to the orientation. Constrained triangulation is performed on the projection. The resulting
145 triangles are labeled based on whether they belong to a particular segment or not. Assume there are n
146 segments in a cluster; each triangle is labeled with a k -dimensional binary vector. The refinement of
147 initial BSS segments is then transformed into a problem of flipping the labels of these triangles.

148 A binary optimization model is formulated for the label flipping. The Boolean variables indicate
149 whether a label should be flipped, or equivalently, a triangle should be removed from or added to a BSS
150 segment. The smoothing and topology refinement are achieved by controlling the label distinctions of
151 triangles distributed across the intersection lines. Adjacent triangles sharing edges on the intersection
152 lines are prone to be labeled differently; that is, if one belong to a BSS segment, the other should not
153 belong to the same BSS segment. For adjacent triangles whose common edges are not on the intersection
154 lines, the optimization model tends to label the two triangles in a same way, i.e., both either belong to
155 or do not belong to a BSS segment. As a result, the optimization encourages continuity inside a BSS
156 segment and discontinuity along the intersection lines, which drives the boundaries of the BSS segments
157 to align with the intersection lines. Additionally, the refinement should not deviate significantly from the
158 initial BSS segments. Therefore, the optimization model also minimizes the number of label flipping.

159 **4 Preliminary experiments**

160 **4.1 Data and implementation details**

161 To validate the initial effectiveness of BSS-Indoor, six samples from the training set of the CV4AEC 3D
162 dataset were tested. Note that this dataset was captured by laser scanners. As a result, there are missing
163 points for walls and outliers outside the buildings due to windows. The six samples include two typical
164 scenarios: office and parking. For the following experiments, the point clouds were uniformly sampled

165 at an interval of 2cm.

166 The semantic point clouds of architectural elements were segmented by PointContrast [14] which
 167 were trained on ScanNet [15] and S3DIS [16]. Plane primitives of the semantic point clouds were de-
 168 tected by RANSAC [17]. We employed K-Means for clustering the plane orientations, where users need
 169 to provide the number of clusters k in advance. In Stage 1, the Alpha shape polygonization of the plane
 170 primitives was implemented based on GEOS [18]. The hyper-parameter α was set to a range from 1 to
 171 3 m. In Stage 2, the constrained triangulation was implemented based on CGAL [19]. The optimization
 172 of integer programming was solved by Gurobi [20] with a weight factor provided by users to balance the
 173 geometric consistency and the degree of alignment.

174 4.2 Evaluation

175 Results were evaluated by the official 3D evaluation code [21] of CV4AEC’s Scan-to-BIM competition.
 176 The evaluation metrics include 3D Intersection-over-Union (IoU) and the matching precision, recall, and
 177 F1-score of the 2D wall segments. Note that the matching of the 2D segments were evaluated at three
 178 different resolutions with matching thresholds of 5, 10, and 20 cm, respectively.

179 4.3 Results

180 The reconstructed volumetric walls and the evaluation results are presented in Fig. 2 and Tab. 1. The
 181 average 3D IoU is 20.4 %, with a range of 7.4 % to 28.7 %. At the 10-cm resolution, the average
 182 precision, recall, and F1 scores are 41.4 %, 41.2 %, and 40.6 %. The precision and recall show a good
 183 balance. The F1-scores at 10-cm resolution range from 21.2 % to 56.1 %. As shown in Fig. 2, some
 184 internal walls and their thicknesses are accurately estimated, as BSS-Indoor captured their dual planes
 185 correctly. The external walls were also partially reconstructed. However, there are still some noticeable
 limitations, particularly for missing walls.

Table 1: Evaluated results of the 6 samples in CV4AEC 3D dataset. #gt, #pred, #m refer to the number of ground truth, prediction (reconstruction), and matched walls, respectively. The matching between 2D wall segments were evaluated with three matching thresholds of 5, 10, and 20 cm.

sample	#gt	#pred	3D IoU	thresh: 5 cm				thresh: 10 cm				thresh: 20 cm			
				#m	prec.	rec.	F1	#m	prec.	rec.	F1	#m	prec.	rec.	F1
06_B1	496	712	7.4%	68	9.6%	13.7%	11.3%	128	18.0%	25.8%	21.2%	172	24.2%	34.7%	28.5%
06_F3	976	856	7.5%	169	19.7%	17.3%	18.4%	217	25.4%	22.2%	23.7%	243	28.4%	24.9%	26.5%
07_F5	904	544	21.0%	198	36.4%	21.9%	27.3%	290	53.3%	32.1%	40.1%	368	67.6%	40.7%	50.8%
32_F1	528	640	31.3%	214	33.4%	40.5%	36.6%	311	48.6%	58.9%	53.3%	340	53.1%	64.4%	58.2%
32_F2	656	688	26.3%	249	36.2%	38.0%	37.1%	333	48.4%	50.8%	49.6%	376	54.7%	57.3%	56.0%
32_F3	688	728	28.7%	301	41.3%	43.8%	42.5%	397	54.5%	57.7%	56.1%	433	59.5%	62.9%	61.2%
Average	/	/	20.4%	/	29.4%	29.2%	28.9%	/	41.4%	41.2%	40.6%	/	47.9%	47.5%	46.9%

186
 187 The current BSS-Indoor implementation failed to reconstruct some external walls. As shown in
 188 Fig .2, such failures are more significant for Samples 06-B1, 06-F3, and 32-F3. This issue occurred
 189 because there might be large empty regions on the external walls where there are large windows. As a
 190 result, holes could be observed in the original scans, semantic point clouds, and the initial alpha polygons
 191 of the plane primitives, making it difficult to reconstruct the external walls.

192 Significant incompleteness in the semantic point clouds and initial alpha polygons also led to the
 193 missing internal walls. These failures could be common due to the heavy occlusions caused by clutter
 194 near the walls.

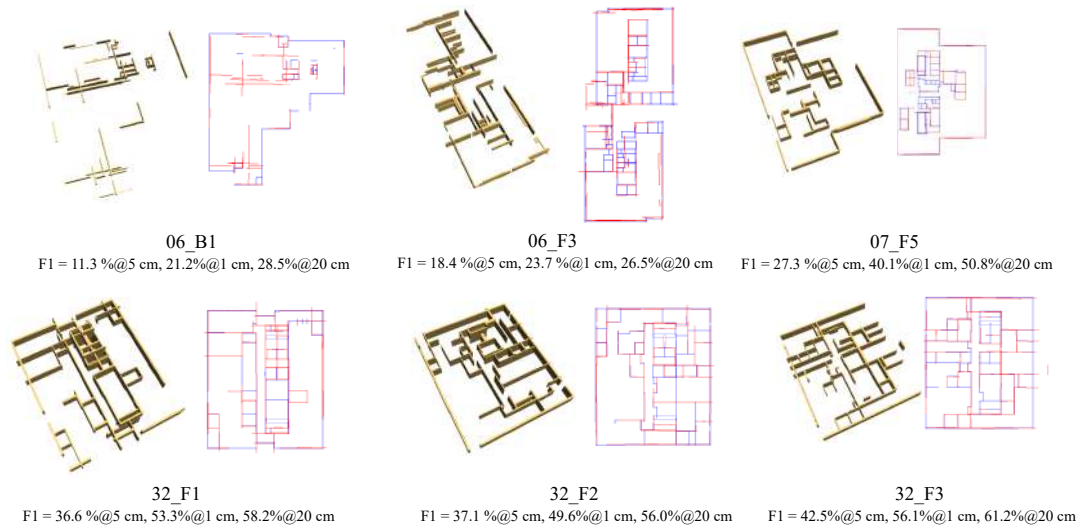


Figure 2: Results of the 6 samples. The right sub-figure for each case displays the matching between the ground truth (in blue) and reconstruction (in red).

5 Discussion

We believe that BSS-Indoor has significant potential in calling for research interest on the volumes of 3D objects above points and triangles. Our method separates the reconstruction of the dual-plane walls (usually internal walls) and single-plane walls (usually external walls), offering higher flexibility in thickness estimation. By distinguishing these two situations, the thickness of a dual-plane wall is calculated as the distance between its paired planes, while the thickness of a single-plane wall can be estimated or assigned by user-specific, average, or standard wall thickness. Furthermore, BSS-Indoor can clearly detect single-plane walls, allowing users to manually review and adjust them if necessary. Importantly, BSS-Indoor does not rely on any learning techniques requiring large-scale manual annotations for thickness estimation, which makes it easier for BIM practitioners to adopt our method in the future.

There are also a lot more details should be improved for the current BSS-Indoor, including (1) fine-tuning the parameters of PointContrast on CV4AEC dataset; (2) adjusting the hyper-parameters of plane detection, Alpha shape polygonization, and the optimization for aligning the BSS segments; (3) debugging the current implementation; (4) testing the method on more samples. Addressing these limitations could lead to enhanced performance and more accurate results.

6 Conclusion

In this paper, we introduced BSS-Indoor, a novel volumetric reconstruction method for walls based on Building Section Skeleton. Our method successfully adapts BSS for building interiors and simultaneously locates and estimates wall thicknesses. BSS-Indoor differentiates between the reconstruction of dual-plane walls and single-plane walls, enhancing the accuracy and flexibility of wall thickness estimation. Preliminary experiments on the CV4AEC (3D) dataset show the effectiveness of BSS-Indoor in reconstructing volumetric walls. Although BSS-Indoor demonstrates potential, further refinement is required to meet the standards necessary for real-world Scan-to-BIM practice in the building sector. Future work will focus on improving the implementation and addressing the limitations identified in the preliminary experiments.

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223 References

- 224 [1] NBIMS-US. National BIM Standard-United States V4. <https://www.nationalbimstandard.org/>,
225 2022. Accessed: 2022-12-29.
- 226 [2] Mansour Esnaashary Esfahani, Christopher Rausch, Mohammad Mahdi Sharif, Qian Chen, Carl Haas, and
227 Bryan T Adey. Quantitative investigation on the accuracy and precision of scan-to-bim under different mod-
228 elling scenarios. *Automation in Construction*, 126:103686, 2021.
- 229 [3] Frédéric Bosché, Mahmoud Ahmed, Yelda Turkan, Carl T Haas, and Ralph Haas. The value of integrating
230 Scan-to-BIM and Scan-vs-BIM techniques for construction monitoring using laser scanning and BIM: The
231 case of cylindrical MEP components. *Automation in Construction*, 49:201–213, 2015.
- 232 [4] Yijie Wu, Maosu Li, and Fan Xue. Towards fully automatic scan-to-bim: A prototype method integrating deep
233 neural networks and architectonic grammar. In *EC3 Conference 2023*, volume 4, pages 0–0. European Council
234 on Computing in Construction, 2023.
- 235 [5] Weilian Song, Jieliang Luo, Dale Zhao, Yan Fu, Chin-Yi Cheng, and Yasutaka Furukawa. A-scan2bim: Assis-
236 tive scan to building information modeling. *British Machine Vision Conference (BMVC)*, 2023.
- 237 [6] Jiali Han, Mengqi Rong, Hanqing Jiang, Hongmin Liu, and Shuhan Shen. Vectorized indoor surface recon-
238 struction from 3d point cloud with multistep 2d optimization. *ISPRS Journal of Photogrammetry and Remote*
239 *Sensing*, 177:57–74, 2021.
- 240 [7] Jiali Han, Yuzhou Liu, Mengqi Rong, Xianwei Zheng, and Shuhan Shen. Floorusg: Indoor floorplan recon-
241 struction by unifying 2d semantics and 3d geometry. *ISPRS Journal of Photogrammetry and Remote Sensing*,
242 196:490–501, 2023.
- 243 [8] Hao Fang, Florent Lafarge, Cihui Pan, and Hui Huang. Floorplan generation from 3d point clouds: A space
244 partitioning approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, 175:44–55, 2021.
- 245 [9] Hao Fang, Cihui Pan, and Hui Huang. Structure-aware indoor scene reconstruction via two levels of abstraction.
246 *ISPRS Journal of Photogrammetry and Remote Sensing*, 178:155–170, 2021.
- 247 [10] Pawel Boguslawski, Sisi Zlatanova, Dariusz Gotlib, Michał Wyszomirski, Miłosz Gnat, and Piotr Grzem-
248 powski. 3d building interior modelling for navigation in emergency response applications. *International*
249 *Journal of Applied Earth Observation and Geoinformation*, 114:103066, 2022.
- 250 [11] Mansour Mehranfar, Alexander Braun, and André Borrmann. From dense point clouds to semantic digital mod-
251 els: End-to-end ai-based automation procedure for manhattan-world structures. *Automation in Construction*,
252 162:105392, 2024.
- 253 [12] Yijie Wu, Fan Xue, Maosu Li, and Sou-Han Chen. A novel building section skeleton for compact 3d recon-
254 struction from point clouds: A study of high-density urban scenes. *ISPRS Journal of Photogrammetry and*
255 *Remote Sensing*, 209:85–100, 2024.
- 256 [13] Iro Armeni, Erzhuo Che, Martin Fischer, Yasutaka Furukawa, Daniel Hall, Jung Jaehoon, Fuxin Li, Michael
257 Olsen, Marc Pollefeys, and Yelda Turkan. Computer vision in the built environment. [https://cv4aec.](https://cv4aec.github.io/)
258 [github.io/](https://cv4aec.github.io/), 2023. Accessed: 2024-3-28.

- 259 [14] Saining Xie, Jiatao Gu, Demi Guo, Charles R Qi, Leonidas Guibas, and Or Litany. Pointcontrast: Unsupervised
260 pre-training for 3d point cloud understanding. In *Computer Vision–ECCV 2020: 16th European Conference,*
261 *Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16*, pages 574–591. Springer, 2020.
- 262 [15] Angela Dai, Angel X Chang, Manolis Savva, Maciej Halber, Thomas Funkhouser, and Matthias Nießner.
263 Scannet: Richly-annotated 3d reconstructions of indoor scenes. In *Proceedings of the IEEE conference on*
264 *computer vision and pattern recognition*, pages 5828–5839, 2017.
- 265 [16] Iro Armeni, Sasha Sax, Amir R Zamir, and Silvio Savarese. Joint 2d-3d-semantic data for indoor scene under-
266 standing. *arXiv preprint arXiv:1702.01105*, 2017.
- 267 [17] Ruwen Schnabel, Roland Wahl, and Reinhard Klein. Efficient ransac for point-cloud shape detection. In
268 *Computer graphics forum*, volume 26, pages 214–226. Wiley Online Library, 2007.
- 269 [18] GEOS contributors. *GEOS coordinate transformation software library*. Open Source Geospatial Foundation,
270 2021.
- 271 [19] Mariette Yvinec. 2D triangulations. In *CGAL User and Reference Manual*. CGAL Editorial Board, 5.6.1
272 edition, 2024.
- 273 [20] Gurobi Optimization, LLC. Gurobi Optimizer Reference Manual. <https://www.gurobi.com>, 2023.
- 274 [21] Sayan Deb Sarkar. 3d building models matching and evaluation code. [https://github.com/cv4aec/](https://github.com/cv4aec/3d-matching-eval)
275 [3d-matching-eval](https://github.com/cv4aec/3d-matching-eval), 2023. Accessed: 2024-3-28.