A hybrid top-down, bottom-up approach for 3D space parsing using dense RGB point clouds

M. Mehranfar, A. Braun & A. Borrmann
Chair of Computational Modeling and Simulation, Technical University of Munich, Germany

ABSTRACT: Nowadays, despite the advanced developments in engineering, automatic large-scale point cloud processing is still one of the challenging topics in many applications. In this regard, segmentation of the indoor point clouds into partitioned spaces is highly demanded in building information modeling (BIM) and robotic society. This paper proposes a novel automatic hybrid top-down, bottom-up approach for the 3D space parsing in the building environment and inferring relations between spaces. The proposed method is based on applying a deep convolutional neural network (CNN) for semantic segmentation of main elements and the use of existing knowledge in the construction of buildings. Unlike the existing methods, the proposed approach does not require pre-knowledge about the space layout. The results of evaluating the proposed method on two datasets with different designs highlight the capability of the proposed approach in 3D space parsing, extracting wall footprints, and particularly finding the topological relation between them.

KEYWORDS: BIM, convolutional neural network (CNN), Point cloud, Segmentation, Top-down approach.

1 INTRODUCTION

With the increase in demands for creating real-world digital twin (DT) models with rich semantic and coherent geometry, the use of 3D data acquisition technologies has increased significantly. Laser scanners and photogrammetry technology are the most modern and efficient measurement tools for providing geometric and semantic information, which is widely used in many fields such as BIM, simulation, navigation, robotics, and facility management (Volk 2014). Besides all the opportunities such as high-density point cloud collection at high speeds and high accuracy, the scanning of large-scale buildings has always been associated with complex layouts of space, clutter, and obstruction (Ochmann, Vock et al. 2015). These have made experts face different challenges in data processing, geometrical modeling, and statistical analysis. Therefore, providing methods for 3D parsing of interior spaces is essential for ideally using large-scale point cloud data.

Defining the space and separating the interior of buildings into distinct spaces (e.g., rooms, corridors, halls, etc.) have different meanings depending on the application and the purpose (Zlatanova, Yan et al. 2020). In the 3D model reconstruction and navigation, an enclosed interior space is defined by main structural elements such as floor, ceiling, and wall, which have topological relations with other connected spaces (Nikoohemat, Peter et al. 2017). In this regard, inferring the prevailing topological relationships between spaces is a practical tool for accurate geometric modeling of complex spaces and simplifying the analysis process in indoor navigation applications (Zlatanova, Liu et al. 2014).

This paper proposes a hybrid top-down, bottom-up approach to alleviate the existing limitations in 3D parsing of the Indoor environment and finding topological relationships between spaces. First, as a top-down approach, the main elements of the building structure, such as walls, and ceilings, are detected using a CNN semantic segmentation method. Then, by neighborhood analyzing the ceiling points at the junction with the wall element and implementing a clustering method, the points of the ceiling element are classified into unique clusters. Finally, the information on clusters is used for disjointing the spaces. The position of common walls in interconnected spaces can express the topological relationships between the spaces in a simple or complex building environment. Due to the complexity of 3D scenes, the extraction of wall elements using previously developed methods has always been associated with challenges such as gaps and noise in the output results. To address this problem, we propose a bottom-up approach to extract the footprints of walls in

a closed space using the existing knowledge in the design and construction of buildings. Finally, after finding the adjacency matrix and the position of common walls between the spaces, the adjacency graph of the building spaces is formed. The structure of the paper is as follows: A brief research background of indoor point cloud segmentation and 3D space parsing is given in Section 2. Next, our proposed framework is explained in Section 3. Section 4 handles the implementation of the proposed algorithm on two different datasets, followed by evaluation and analyses of our results. A conclusion and discussion about the results are presented in Section 5.

2 RELATED WORK

Developing an automatic and robust algorithm for partitioning large-scale indoor point clouds into individual spaces is a topic that has long been researched and studied. Generally, the previously developed methods have tried to use the structural-architectural definitions of buildings for segmenting the spaces. They mainly employed various techniques and assumptions to detect the walls of space separators.

In constructing 3D building models based on the BIM concept, Xiong et al., (Xiong, Adan et al. 2013) separated the spaces in an indoor environment using an assumption of the similarity of planar surfaces. Mura et al., (Mura, Mattausch et al. 2014) used an occlusion-aware approach by employing knowledge of laser scanner locations to separate spaces and reconstruct complex indoor spaces. Ochmann et al. proposed an iterative clustering algorithm that uses the probability of affiliation of each point to an individual room by estimating the visibilities between any two locations (Ochmann, Vock et al. 2014).

In some developed methods, the researchers focused on utilizing tools such as RGB image features (Ren, Bo et al. 2012), depth features (Silberman, Hoiem et al. 2012), or floor plan maps (Liu, Schwing et al. 2015) to simplify the problem of identifying planar walls and separating spaces in buildings with complex designs. Ochmann et al., (Ochmann, Vock et al. 2015) presented an automatic approach for parametric modeling of the building, which detects the wall elements shared between rooms by solving a labeling problem and implementing an energy minimization optimization. To improve the previous methods, Ochmann et al., (Ochmann, Vock et al. 2019) used the RANSAC plane detection algorithm and an integer linear optimization problem to develop a fully automatic room segmentation. Armeni et al. (Armeni, Sener et al. 2016) proposed a density-based histogram analysis for 3D space parsing. They divided a whole point cloud of the indoor scene into disjoint spaces (i.e.,

the floor plan), which afterward the information such as spaces adjacency can easily be reached.

According to what was examined, most of the developed methods for 3D space parsing required pre-knowledge about the layout of spaces or the location of laser scanners. They can only be considered for small-scale environments. In addition, the output of unsupervised segmentation methods that use features such as density to separate spaces is always associated with threats such as over-segmentation.

Examining all aspects and limitations of developed methods, we propose an automated knowledge-based algorithm that utilizes artificial intelligence capacities and knowledge in building structural design to minimize the effects of challenges. Our focus is on separating spaces in real-world built environments with any simple/complex layout designs. More details about the proposed methodology are provided in the next section.

3 METHODOLOGY

As shown in Figure 1, the proposed method includes three major steps including; 1) semantic segmentation of point cloud to extract the main elements (e.g., walls, ceiling), 2) point neighborhood analysis and performing density-based clustering algorithm, 3) Walls footprint extraction using principal component analysis (PCA). The details of the steps are given in the following subsections.

3.1 *Semantic segmentation of point cloud*

The first step in the proposed method is the semantic segmentation of the indoor point cloud and separating elements that constitute the structure of the building. Ceilings and walls are the major part of any building, which have important rules in space layout and design. In a building, each space is surrounded by interior and/or exterior walls, and generally, the Interior walls are a common part between two or more spaces. Due to the complexity of indoor scenes and point cloud challenges, accurate extraction of the planar elements such as walls and ceilings using the traditional unsupervised method is a problematic and costly computational task. Also, these methods often need to define a set of prerequisites parameters for each case, which reduces the automation level of algorithms.

With the ongoing development of deep learning concepts in the last decade, large-scale data classification and segmentation have become one of the most prevalent research aspects in computer vision and construction society. We use the unique capabilities of artificial intelligence (AI) methods for semantic segmentation of large-scale point cloud data and extract wall and ceiling elements in complex and cluttered building environments.
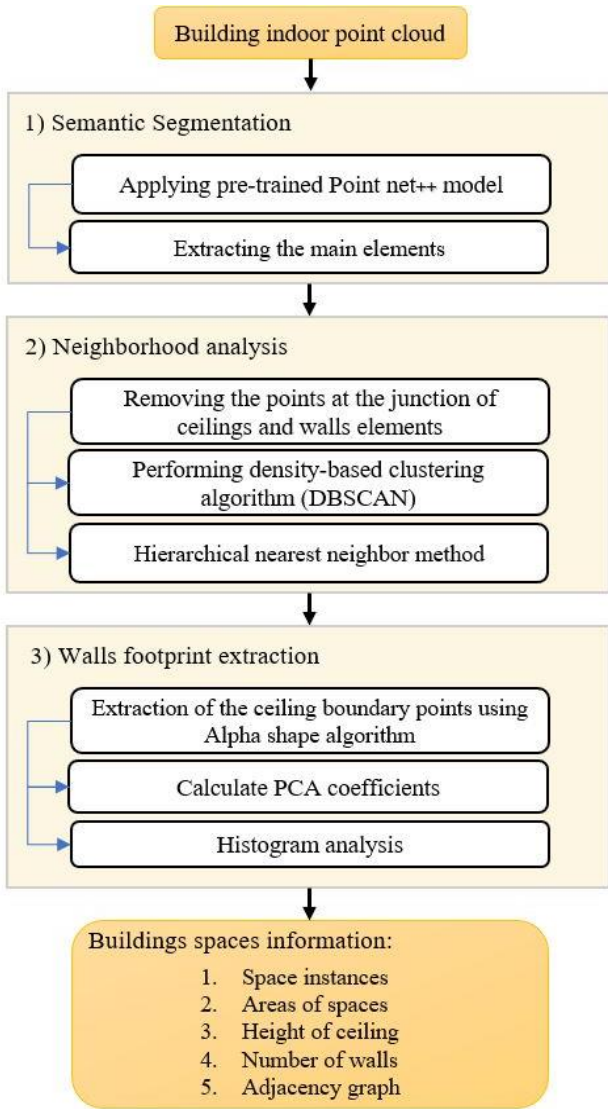
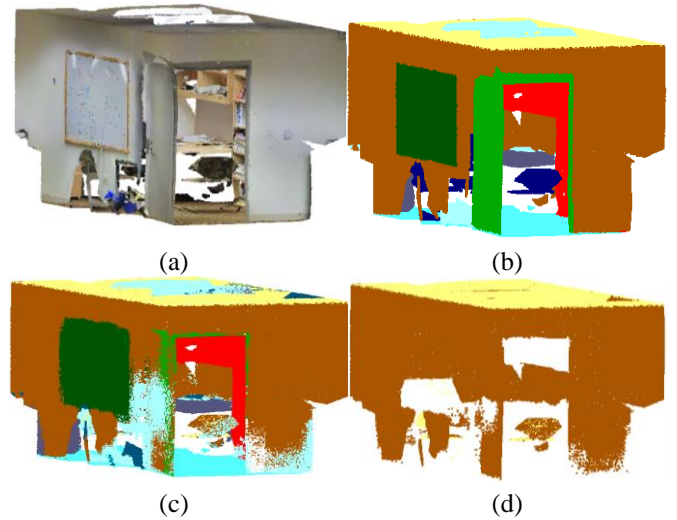Figure 1. Proposed workflow for 3D parsing of indoor spaces and extracting corresponding walls footprints.

Figure 2. Semantic segmentation of S3DIC dataset using PointNet++ model, (a) RGB point cloud, (b) ground truth, (c) result of semantic segmentation, and (d) extracted ceiling and walls elements.

In this case, we use a pre-trained semantic segmentation model based on the PointNet++ network (Ruizhongtai Qi, Yi et al. 2017). The PointNet++ architecture considers connectivity between points to extract local/global detailed geometrical features through multi-scale regions and hierarchical aggregation. The main focus of this step is on detecting wall and ceiling points for disjointing the 3D spaces. Thus, we use the semantic segmentation network trained with the S3DIC dataset, a well-known dataset of indoor space of buildings with thirteen object classes (e.g., ceiling, floor, wall, and furniture) (Armeni, Sax et al. 2017) (figure 2).

3.2 *Neighborhood analysis and points clustering*

Obviously, in the buildings, the ceiling and wall elements are mounted vertically on each other and have a common boundary. Also, when generating point clouds using laser scanners and camera sensors, a gap always appears in the part of the common wall between the two spaces. This knowledge provides key clues to separate the spaces from each other.

An enclosed indoor space consists of basic structural elements such as floor, ceiling, and wall. To find the central part of an individual enclosed space surrounded by walls, the neighborhood of the ceiling points at the junction with the wall element is analyzed. So, each ceiling point in *th* distance from the wall points is removed from the ceiling segment. The value of *th* is based on the average thickness of interior walls in the type of buildings considered. After that, the ceiling point clouds become a set of scattered segments far from the walls separating the space. Subsequently, a clustering method can turn the remaining points of the ceiling element into unique segments (figure 3). These segments are the central part of the space ceilings that are now separated and get their unique labels. In this regard, the density-based clustering algorithm (DBSCAN) is recommended for clustering the scattered points (Ester, Kriegel et al. 1996). The DBSCAN algorithm clusters the points by assuming that clusters are dense point groups in space within a specific range (a certain neighborhood radius) separated by lower density groups. The efficiency in dealing with noisy data is one of the outstanding features of DBSCAN.

Eventually, a hierarchical nearest neighbor method assigns the correct cluster label to the re-

moved ceiling points (figure 4). All clusters' points are used to find the nearest point to the removed ceiling points in this process.
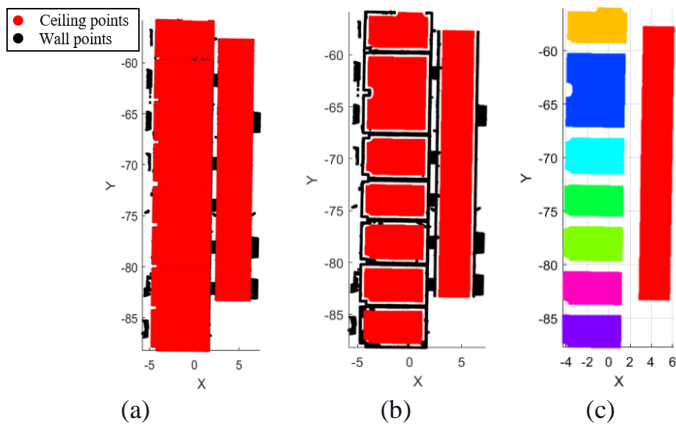

Figure 3. Overview of the proposed algorithm for 3D space parsing, (a) ceiling and walls points, (b) removing ceiling points at *th* distance from walls, and (c) clustering remaining ceiling points using the DBSCAN algorithm.
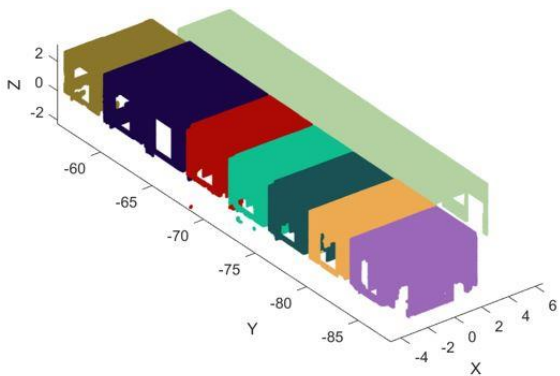

Figure 4. Applying the nearest neighbor method to assign cluster-ID for removed ceiling points.

3.3 *Walls footprint extraction*

The similarity of geometric and spectral features of wall points with other elements in the building environment leads to the fact that detecting wall surface points using deep learning methods would not be without error. As accurate wall positioning is an important and highly demanded task in many applications such as digital twinning, path planning, etc., we combine the bottom-up knowledge-based approach with the capabilities of deep learning networks to reach a high accuracy in detecting the location of walls. Based on the research, the detection of ceiling and floor points has the highest accuracy toward the whole elements in all developed semantic segmentation models (Table-1) (Hu, Yang et al. 2019). Also, the ceiling and wall elements have a common outer and inner boundary in an enclosed space. We can use boundary points of the ceiling to extract the footprint of the walls belonging to each 3D space. In a closed space consisting of several intersecting walls, changes in the PCA parameters indicate breakpoints or abrupt changes. These abrupt changes are for the endpoints of each wall where the curvatures are changed.

To make it clearer, first, the boundary points of ceilings are extracted using the Alpha shape (Edelsbrunner, Kirkpatrick et al. 1983), and MeanShift (Cao, Qiu et al. 2019) methods, and then points are sorted in the x-y plane using the traveling salesman problem (TSP) (Sangwan 2018). This increases the accuracy of the calculation of PCA values and leads to control over the data when finding the location of the abrupt changes. Next, the PCA coefficients are calculated for each point by considering *n* sorted neighbor points. We apply a histogram analysis to the real part of PCA coefficients values to find the locations of abrupt changes in PCA values. The points between two consecutive breakpoints belong to the surface of a wall. Finally, the points belonging to each wall in the 3D space are extracted from the original point cloud by considering a buffer around the separated points (figure 5).
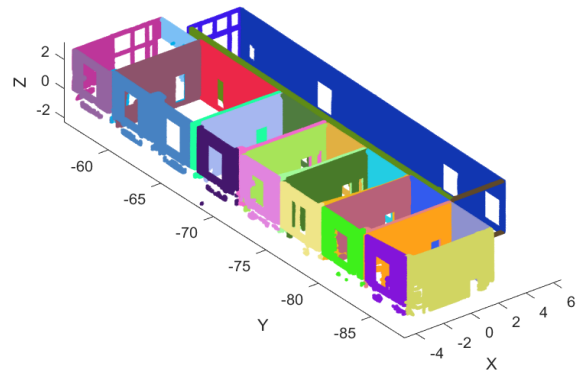

Figure 5. Extraction walls footprint using the proposed method.

3.4 *Creation adjacency graph*

Individual spaces are separated by common walls or connected by openings like doors/windows in an indoor environment. An adjacency graph represents the adjacency relationships plan of all spaces that are not necessarily connected, which can provide different processing possibilities in applications such as BIM, robotics, path planning, etc. The adjacency graph G is defined by G (V, E), in which Vertices (or nodes) of a graph are individual spaces, and Edges present adjacency between two distinct spaces. Accordingly, the method of calculating the distance between the point cloud of space instances with a *th* neighborhood tolerance is used to find the adjacency relationships (figure 6). Also, the location of common walls, which indicates the connection between two spaces, can easily be handled by calculating the distance between all walls in two adjacency spaces and checking the parallelity conditions of the lines passing through the candidate wall's points.

Table 1. Quantitative results of different approaches on S3DIS (6-fold cross-validation) (Hu, Yang et al. 2019), the difference between the accuracy of detection ceilings and wall points.

|	OA (%)	mAcc (%)	mIoU (%)	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book	board	clut.
PointNet	78.6	66.2	47.6	88.0	88.7	69.3	42.4	23.1	47.5	51.6	54.1	42.0	9.6	38.2	29.4	35.2
RSNet	-	66.5	56.5	92.5	92.8	78.6	32.8	34.4	51.6	68.1	59.7	60.1	16.4	50.2	44.9	52.0
3P-RNN	86.9	-	56.3	92.9	93.8	73.1	42.5	25.9	47.6	59.2	60.4	66.7	24.8	57.0	36.7	51.6
SPG	86.4	73.0	62.1	89.9	95.1	76.4	62.8	47.1	55.3	68.4	**73.5**	69.2	63.2	45.9	8.7	52.9
PointCNN	**88.1**	75.6	65.4	**94.8**	**97.3**	75.8	63.3	51.7	58.4	57.2	71.6	69.1	39.1	61.2	52.2	58.6
PointWeb	87.3	76.2	66.7	93.5	94.2	80.8	52.4	41.3	64.9	68.1	71.4	67.1	50.3	62.7	62.2	58.5
ShellNet	87.1	-	66.8	90.2	93.6	79.9	60.4	44.1	64.9	52.9	71.6	**84.7**	53.8	64.6	48.6	59.4
KPConv	-	79.1	**70.6**	93.6	92.4	**83.1**	**63.9**	**54.3**	**66.1**	**76.6**	57.8	64.0	**69.3**	**74.9**	61.3	**60.3**
RandLANet	88.0	**82.0**	70.0	93.1	96.1	80.6	62.4	48.0	64.4	69.4	69.4	76.4	60.0	64.2	**65.9**	60.1

(a)   (b)
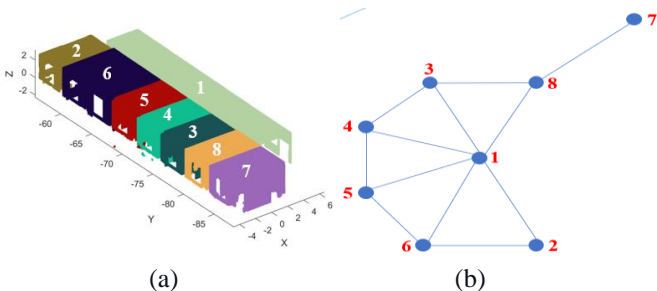
Figure 6. Creation of the adjacency graph, (a)3D individual spaces, (b) corresponding adjacency graph.

4 RESULTS AND DISCUSSION

4.1 *Case Study*

To validate the performance of the proposed method, we considered two building dense point clouds with different space layouts (figure 7). The first is the S3DIC area 5 dataset. The building is mainly for educational and office use and contains different enclosed 3D spaces (e.g., hallway, office, storage, etc.). The second dataset is a part of building No.1 of the Technical University of Munich. Ground truths for 3D space parsing are available for both raw point cloud data. Apart from that, some statistical information about the structural design of the buildings has been provided by the facilities department which have been reported in Table 2.
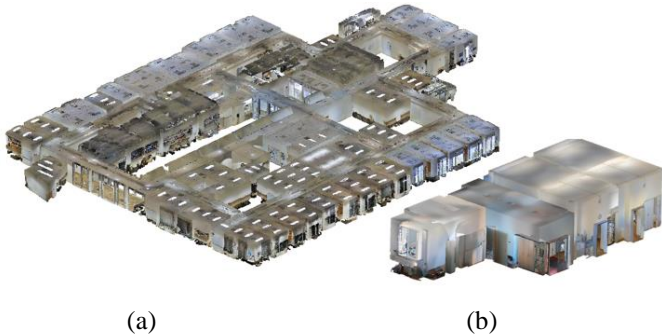

(a)   (b)

Figure 7. Overview of the data: (a) Stanford building, (b) TUM building.

Table 2. Statistics information on buildings.

Dataset	Area (m^2)	Number of spaces	Number of walls	Number of points
Stanford building	1700	55	344	78.649.818
TUM building	99.60	4	16	16.529.431

4.2 *Experimental results of point cloud semantic segmentation*

As mentioned in section 3.1, we used the Point-Net++ pre-trained network for the semantic segmentation task. The model has been trained using the S3DIC dataset, including; Area 1-4 and Area 6. These datasets include 210 individual spaces from three educational buildings with different architectural features. Table 3 shows more details about the parameters used in network training. We tested the model on both cases study datasets. The general metrics, Intersection-Over-Union (IOU) per class, the average accuracy of the classes (mAcc), and overall accuracy of points (OA) were calculated to evaluate the performance of the semantic segmentation step which have been reported in table 4. As stated before, the purpose of the semantic segmentation step is to extract the main elements of the building space, including ceilings and walls. In this regard, an average IOU of about 88.56% for detecting ceiling, floor and walls elements highlights the efficiency of the used semantic segmentation model.

Table 3. Parameters of pre-trained semantic segmentation network using Point Net++ model.

Parameter	value
Batch size	16
Number of points per voxel	4096
Epoch	128
Learning rate	0.001
Decay rate	0.0001
Learning rate decay	0.7

Table 4. Quantitative results of the semantic segmentation datasets using PointNet++ network.

Building	OA (%)	mAcc (%)	mIoU (%)	(IOU) per class												
				ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book	board	clut.
Stanford	82.98	62.02	53.53	89.4	97.7	75.4	0	1.8	58.3	19.5	69.2	79.0	46.2	59.1	58.7	41.6
TUM	86.53	69.7	55.92	91.3	96.4	81.2	0	2.6	53.9	27.1	73.3	75.7	52.5	58.7	61.5	53.7

As reported in Table 1, the averages of the models' IoU value in detecting the ceiling and wall elements are 92.05% and 77.51% respectively, which is somewhat equal to the accuracy obtained in the PointNet++ model. The low accuracy in the detection of walls depends on various factors such as the scene's complexity and the use of different materials in the design (e.g., glasses, wood, etc.), which are inevitable in building environments. Addressing this problem requires preparing huge different datasets to achieve excellent performance, and collecting such data for buildings with cluttered scenes is highly expensive and challenging. These problems place limitations on all developed models. Therefore, once again, the importance of addressing the existing knowledge in building design and element interaction for use in processes related to feature extraction and modeling tasks is highlighted.

4.3 Experimental results of 3D space parsing and walls footprint extraction

To disjoint 3D spaces, first, the points of the ceiling element at the 40 cm distance from the wall element were removed from the ceiling segment. Considering the value of 40 cm as the distance threshold was based on the average thickness of the interior-exterior walls in office building design with any material such as concrete, stone slab, etc. After that, the DBSCAN clustering method and the nearest neighbor algorithm were applied to cluster 3D space points into the different groups (figure 8).

After separating the 3D spaces, the ceilings boundary points were extracted and then point sorted in the X-Y plane with the TSP algorithm. Next, the PCA coefficient was calculated for each point by considering 25 neighbor points. Subsequently, the location of walls footprints in each space instance was detected by finding abrupt changes in the histogram of the real part of corresponding PCA coefficients (figure 9). Eventually, to extract the points belonging to walls in XYZ space, a 2.5 cm buffer was considered around the footprints, and then the inlier points were extracted from the original point cloud (figure 10).
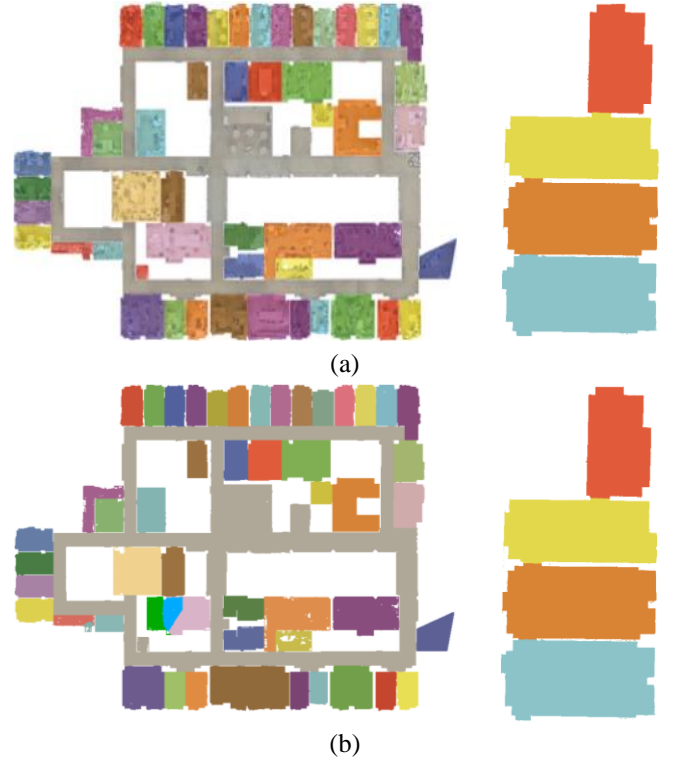

(a)

(b)

Figure 8. 3D space parsing: (a) Ground truth, (b) The result of proposed method, left; Stanford building, and right; TUM building.
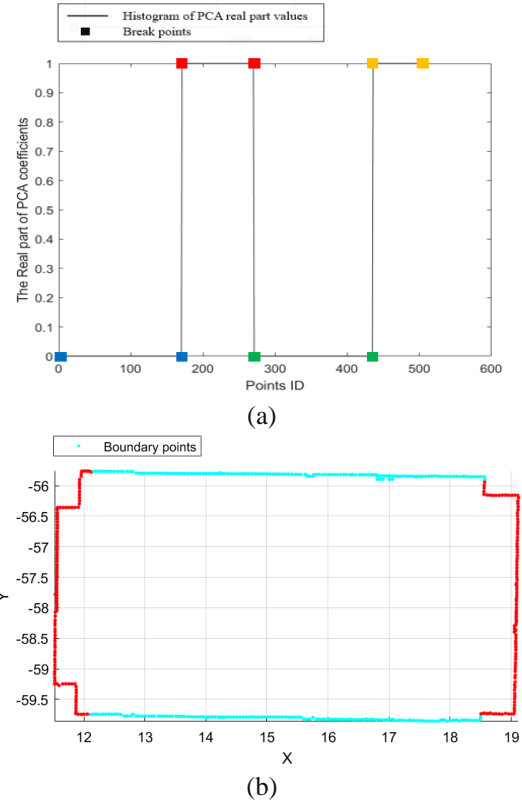

(a)

(b)

Figure 9. Walls separation, (a) detecting wall endpoints using histogram analysis of PCA coefficients, and (b) separating walls using breakpoints.
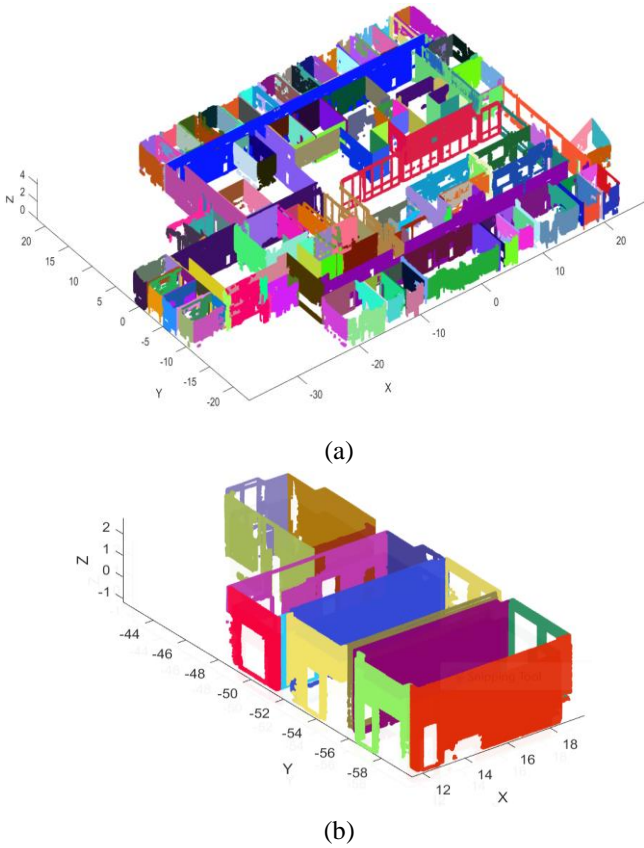
(a)

(b)

Figure 10. Wall points extraction using the proposed method: (a) Stanford building, (b) TUM building.

To find the adjacency relations of spaces according to indoor layout, the distance between all the segmented spaces was calculated, and considering a 40 cm tolerance as the neighborhood confidence distance, the adjacency graph of the spaces was formed for building datasets. Figure 11 shows the generated adjacency graphs.

In order to investigate the performance of the proposed algorithm for 3D space parsing and extraction of the corresponding walls, a quantitative evaluation between the statistical parameters of the result and the information reported by the facilities department is considered (Table 5). These include; the calculation of the standard unsupervised clustering metric Rand Index (RI) (Rand 1971), the number of individual spaces, and the number of walls per space. Also, an average distance between the extracted wall points cloud and ground truths' wall points is calculated for each building dataset. In this regard, the overall accuracies for 3D space parsing and extracting the number of the corresponding walls are 96.25% and 95.21%, respectively, which indicates the utility of the proposed algorithm. One of the most important challenges in 3D space parsing in a large-scale indoor environment is the separation of hallways from each other and solving their over-segmentation problem. In contrast, the hallways are connected and form a space in a building. As can be

seen in the results, our proposed knowledge-based algorithm can solve this problem well and separate hallways and corridors into one space without any post-processing task.
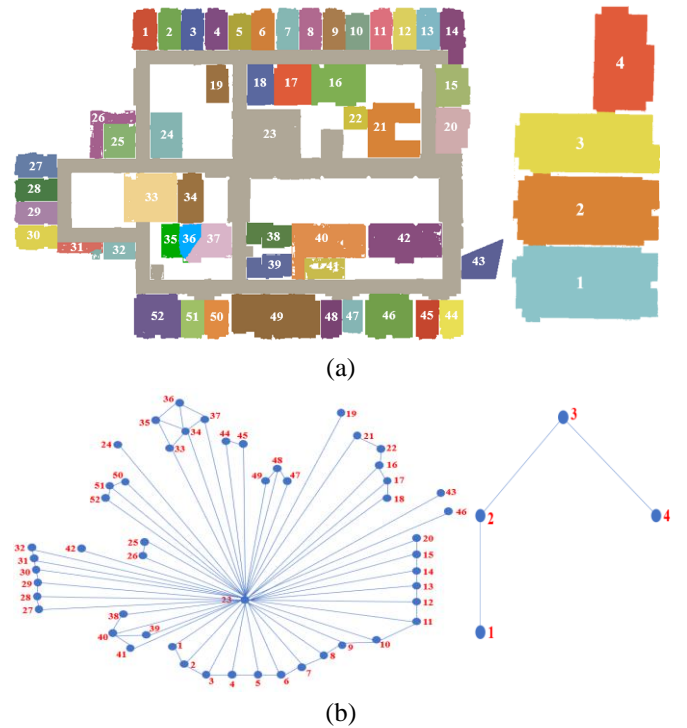

(a)

(b)

Figure 11. Adjacency graph of spaces: (a) Spaces, (b) created adjacency graph, left; Stanford building, right; TUM building.

Table 5. Quantitative results of the proposed algorithm for 3D space parsing and walls extraction.

	Rand Index (RI) (%)	Number of Spaces (%)	Number of walls per space (%)	C2C distance between walls points (cm)
Stanford building	93.61	94.55	90.43	12
TUM building	98.9	100	100	2
Overall	96.25	97.27	95.21	7

5 CONCLUSION

This paper presents a novel hybrid bottom-up-top-down algorithm for automatic 3D space parsing in the built environment. The main idea of the proposed approach is to combine the capabilities of AI methods and knowledge in the building's design to overcome the limitations of common traditional methods of point cloud processing, such as determining variable parameters and over-segmentation. Also, the hybrid approach improves automation and efficiency in the face of all real-world building designs such as Manhattan and non-Manhattan layouts. To improve the algorithm's performance in prevail-

ing challenges such as noisy point clouds with clutter in the complex buildings' indoor scenes, PointNet++ semantic segmentation model is implemented and its results for wall and ceiling detection are used for the 3D space parsing. The accuracies of 97.27% for the segmentation of 3D spaces and 95.21% for the extraction of the corresponding walls prove the high performance of the proposed algorithm in the face of buildings with any simple or complex design. Unlike other developed methods, our proposed approach does not require prior knowledge, such as the layout of indoor environments, sensors' location, etc., to separate the spaces. Segmentation of indoor point clouds into partitioned spaces paves the way for novel industrial applications such as building space statistics analysis and manipulation. In particular, the real-time space parsing by simplifying the large-scale data processing is an important and effective leap in the robotic application for the built environment which makes it feasible in specific usage such as facility management, path planning, etc. One of the main goals of constructing digital twin models based on BIM concepts is to provide geometric and semantic information about an object simultaneously. As the outputs are partitioned 3D spaces and corresponding wall instances, it is easily possible to infer any statistical information (e.g. area, volume, height, etc.) and also the topological relationship between them, which allows the independent use and processing in many applications such as; scan to BIM, 3D modelling, and navigation.

ACKNOWLEDGMENT

REFERENCES

Armeni, I., A. Sax, A. Zamir and S. Savarese (2017). "Joint 2D-3D-Semantic Data for Indoor Scene Understanding."

Armeni, I., O. Sener, A. Zamir, H. Jiang, I. Brilakis, M. Fischer and S. Savarese (2016). 3D Semantic Parsing of Large-Scale Indoor Spaces.

Cao, X., B.-Z. Qiu and G. Xu (2019). "BorderShift: toward optimal MeanShift vector for cluster boundary detection in high-dimensional data." Pattern Analysis and Applications 22.

Edelsbrunner, H., D. Kirkpatrick and R. Seidel (1983). "On the shape of a set of points in the plane." Information Theory, IEEE Transactions on 29: 551-559.

Ester, M., H.-P. Kriegel, J. Sander and X. Xu (1996). A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise.

Hu, Q., B. Yang, L. Xie, S. Rosa, Y. Guo, Z. Wang, N. Trigoni and A. Markham (2019). RandLA-Net: Efficient Semantic Segmentation of Large-Scale Point Clouds (CVPR 2020 Oral).

Liu, C., A. Schwing, K. Kundu, R. Urtasun and S. Fidler (2015). Rent3D: Floor-plan priors for monocular layout estimation.

Mura, C., O. Mattausch, A. Jaspe-Villanueva, E. Gobbetti and R. Pajarola (2014). "Automatic Room Detection and Reconstruction in Cluttered Indoor Environments with Complex Room Layouts." Computers & Graphics.

Nikoohemat, S., M. Peter, S. Oude Elberink and G. Vosselman (2017). "EXPLOITING INDOOR MOBILE LASER SCANNER TRAJECTORIES FOR SEMANTIC INTERPRETATION OF POINT CLOUDS." ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences IV-2/W4: 355-362.

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

Ochmann, S., R. Vock, R. Wessel and R. Klein (2015). "Automatic Reconstruction of Parametric Building Models from Indoor Point Clouds." Computers & Graphics 54.

Ochmann, S., R. Vock, R. Wessel, M. Tamke and R. Klein (2014). "Automatic generation of structural building descriptions from 3D point cloud scans." GRAPP 2014 - Proceedings of the 9th International Conference on Computer Graphics Theory and Applications: 120-127.

Rand, W. (1971). "Objective Criteria for the Evaluation of Clustering Methods." Journal of the American Statistical Association 66: 846-850.

Ren, X., L. Bo and D. Fox (2012). RGB-(D) scene labeling: Features and algorithms.

Ruizhongtai Qi, C., L. Yi, H. Su and L. Guibas (2017). "PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space."

Sangwan, S. (2018). "Literature Review on Travelling Salesman Problem." International Journal of Research 5: 1152.

Silberman, N., D. Hoiem, P. Kohli and R. Fergus (2012). Indoor Segmentation and Support Inference from RGBD Images.

Volk, R. S., Julian & Schultmann, Frank. (2014). "Building Information Modeling (BIM) for existing buildings — Literature review and future needs." Automation in Construction 38: 109–127.

Xiong, X., A. Adan, B. Akinci and D. Huber (2013). "Automatic Creation of Semantically Rich 3D Building Models from Laser Scanner Data." Automation in Construction 31: 325–337.

Zlatanova, S., L. Liu, G. Sithole, J. Zhao and F. Mortari (2014). Space subdivision for indoor applications.

Zlatanova, S., J. Yan, Y. Wang, A. Diakite, U. Isikdag, G. Sithole and J. Barton (2020). "Spaces in Spatial Science and Urban Applications-State of the Art Review." International Journal of Geo-Information 9: 58.