A Top-Down Hierarchical Approach for Automatic Indoor Segmentation and Connectivity Detection

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Abstract:
Data organization is essential for effective analysis of the spatial relationships between rooms and walls. Segmentation in successive stages plays a crucial role in this process since dividing the data set into smaller sets makes its analysis easier. The proposed approach starts with the segmentation of buildings by storeys using a three-dimensional point cloud and is carried out by detecting peaks in histogram of Z frequency. Subsequently, each storey is segmented into rooms using three-dimensional mathematical morphology techniques, which allows the delimitation of the interior spaces. The third and final step consists of identifying elements within each room, such as doors, ceiling, floor, and walls. During this process, connectivity and adjacency of building elements are studied to automatically derive topological graphs. This methodology results in a deeper and more systematic analysis of three-dimensional spaces, providing a solid basis for the subsequent interpretation and manipulation of the data obtained. The proposed method has been tested in two real cases and the results are shown respectively.

1. Introduction

The construction industry, when compared to sectors like media, finance, and others, continues to be one of the least digitized industries (Hu et al., 2022), resulting in its well-documented issues with project delivery and meeting budgets. In research conducted by KPMG (2015), Multiproject (2021) and GoCodes (2023) the organizations found that major hurdles are present in the pursuit of successful projects. KPMG says over 50% of organizations had a project underperform while only 25% were completed within 10% of the original deadline. GoCodes reported that 60% of contractors experienced project delays and 50% of projects were completed within their timeframe and budget. Further, Multiproject found 69% of projects exceeding their budgets by more than 10%, impacting both profitability and completion. To address these challenges, the construction industry has increasingly adopted Building Information Modeling (BIM). BIM captures a building's lifecycle digitally, including 3D design, materials, and crucial data.

Scan-to-BIM is one of the main current trends in digital construction. It consists in a process that converts point cloud data from laser scanning and photogrammetry into detailed 3D models of existing building, encompassing both Manhattan (arranged along orthogonal directions and right angles) and non-Manhattan World structures (lacks rigid regularities, displaying diverse shapes, irregular arrangements, and varied orientations). Recognizing this difference between MW and non-MW structures is crucial for selecting appropriate processing techniques, segmentation strategies and modelling approaches.

The process of Scan-to-BIM has typically multiple stages, including data capturing, which involves obtaining precise geometrical details about the real world surrounding using technologies such as Light Detection and Ranging (LiDAR) scanners or photogrammetry and may require data registration to align several scans within one coordinate system. Subsequent, pre-processing steps are performed to clean and prepare the raw point cloud data for further analysis. This may involve noise removal, outlier detection, and data normalization to ensure accuracy and reliability. Segmentation techniques are then used to divide point cloud into meaningful subsets based on shared characteristics such as geometric properties or semantic attributes. In some instances, classification or semantic segmentation methods are employed to label individual point's enrichment the data with meaningful contextual information.

Even though it has a promising potential, Scan-to-BIM approaches have their own challenges. For instance, most Scan-to-BIM efforts heavily depend on manual labelling (Xiong et al., 2023) which results in a lack of robustness between models and their corresponding buildings. One major hurdle is how to effectively process large amounts of point-cloud data in an efficient manner given the complexity and size of the data. Moreover, occlusions, environmental factors and inconsistencies in data quality can hinder interpretation and processing considerably.

In response to these challenges, this paper proposes a top-down hierarchical approach for the automatic segmentation of indoor point clouds, enabling the direct retrieval of topological graphs. The method is based on the implementation of 3D mathematical morphology and relies on the study of the indoor empty space. Unlike individual building elements like walls, ceilings, and floors, rooms constitute a higher-level hierarchical structure that provides insight into the configuration of indoor environments, and doors represent the connection between spaces. This information plays a vital role in the comprehension of indoor space configuration, which is fundamental for reconstructing topologically-coherent models, and for performing tasks related with indoor navigation and path-finding. In this context, the contribution of this research lies in two key aspects:

(1) A 3D mathematical morphology strategy for room and door segmentation based on the study of the empty space.
(2) A top-down approach enabling the automatic retrieval of topological relationships.

This paper is organized as follows: Section 2 provides a comprehensive review of indoor point cloud segmentation and topology extraction focused on rooms and doors. Section 3 elaborates on the developed approach, while Section 4 shows the experiments and results obtained from applying the method to real case studies. Lastly, Section 5 is devoted to conclude this work.

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2. Related Work

2.1 Room segmentation

In the realm of indoor building analysis, while numerous segmentation strategies have been developed for directly classifying building elements such as walls, ceilings, floors, windows and furniture, most existing literature primarily focuses on directly segmenting detected building components using various techniques such as Point-to-point, Point-to-surface, or taking advantage of different object's features (Hu & Brilakis, 2024). However, there is a notable gap in addressing room segmentation specifically. Many authors take several main assumptions when detecting the permanent structures (Nikoohemat el al., 2020). As an example, a segment would be categorized as a floor if its normal direction is vertical, its 2D area exceeds a specific threshold and its height is below the average z-value of a point cloud (Xiong et al., 2023).

Many authors have developed different methods to assess room segmentation, for example, Frías et al. (2020) convert point clouds in voxels to extract indoor empty spaces by the building contour, and they apply 3D morphological erosion to identify empty spaces by room semantics and morphologically dilate by segmentation of a point cloud. In contrast, Mura et al. (2014) developed an algorithm to process 3D point cloud data of indoor spaces that makes the assumption of vertical walls in consistent registration, to generate polygonal representations for closed of each room by combining 3D and 2D operations. Nikoohemat et al. (2020) employed regularized Boolean operations on reconstructed permanent structures to delineate room volumes, integrating semantic information for flexible space subdivision. Ochmann et al. (2016) introduced a segmentation technique that need prior information about the scanning positions and is grounded in Bayesian theory, where the quasi-conditional probability is computed by considering the mutual visibility of points and iteratively adjusting point allocations within rooms. In comparison, Xiong et al. (2023) method does not require any prior knowledge and is based on the assumption that a room is an enclosed space surrounded by the main structure of a building. First the point cloud is semantically segmented into different components (walls, beams, floors, ceilings, and clutters) and wall-beam centreline is employed and segmented for then refined using an optimization method.

2.2 Door segmentation

In the context of analysing an indoor environment, door detection is a critical component that has applications in navigation systems, building mapping, and even interior design because they act as the connecting element between adjacent rooms (Frías et al., 2020). Detecting doors is easy when they are open, as they create a hole in the wall. However, when closed, detection becomes more challenging due to the lack of descriptive features because objects with similar sizes and shape to doors can be mistakenly identified as doors, increasing false positives (Flikweert et al., 2019). For example, Díaz-Vilariño et al. (2015) developed an image-based algorithm utilizing the Generalized Hough Transform (GHT) for identifying potential door locations within orthoimages. Then Díaz-Vilariño et al. (2016) determined wall planes treating them as binary images where pixels indicate one or zero depending on whether points fall inside the pixel or not. However, these methods rely on predefined door sizes and shapes and are also vulnerable to detecting false positives. To address this challenge, if a MLS is used for data capture, trajectory can be used to help in the process of door detection. For instance, Nikoohemat et al al. (2018) utilize ray-casting from the trajectory to recognize apertures in walls, classifying holes as a door when the trajectory passes nearby its midpoint. Other approaches can only detect doors passed through. Flikweert et al. (2019) implement the 3DMAT algorithm which allows for the generation of medial sheets that can act as dividers between furniture, walls and voids within walls. It is aimed at creating spaces in indoor environment for voxel detection and separate floor regions. In Elseicy et al. (2018), the trajectory is employed to highly accurate localization of potential door locations after extracting laser points in close proximity and then checking the door width along the trajectory, thus enabling detection of opened, semi-opened, and closed doors during scanning. In Díaz-Vilariño et al. (2017), doors are detected by extracting a vertical profile of the point cloud along the trajectory followed by the MLS but is limited to doors that are not at the same height as the ceiling. Another approach detects open doors and door passes from a voxel-based labelling approach (Okorn et al., 2010), where doors are considered as openings in the wall structures.

2.3 Connectivity detection

In 2014, the Open Geospatial Consortium (OGC) standardized IndoorGML with the Node-Relation Graph (NRG) to model indoor spaces for navigation. The graph models represent the geometric relationships between rooms and corridors, which are crucial for understanding indoor layouts and developing navigation and mapping algorithms. These relationships can be classified into three categories: Adjacency, Connectivity, and Accessibility. Adjacency specifies edges between two adjacent spaces, Connectivity specifies edges between two spaces connected by doors, and Accessibility provides information on traversability. NRGs can either use a thin wall model where spaces are nodes, and edges link spaces to one to the other, or a thick wall model where spaces are nodes; there are also nodes for walls and doors to enhance navigation knowledge (Flitweert et al., 2019). In connectivity graphs, walls are normally removed, and the doors remain as nodes. Connectivity graphs are pivotal and it is on the process of graph extraction from point cloud processing that the true potential of indoor navigation emerges. Nikoohemat et al. (2020) enhanced indoor navigation by including features like doors and stairs in the graph, facilitating route planning. Flitweert et al. (2019) check connectivity algorithmically by door, stair, and slope nodes. It is assumed that the whole interior is connected with doors, stairs, and slopes. Stairs and slopes link to spaces or doors at the bottom and the top node, while the doors link two spaces or a floor and a stair/slope. A network arises by connecting points within spaces to points of doors and stairs. Drobnyi et al. (2024) classifies the connectivity between surface pairs from point cloud data directly using the PointNeXt-based model, addressing imbalance through filtering methods like Neighbour connection and Line-cast-based rejection. Tran et al. (2017) establishes connectivity between shapes based on adjacency and interior classification guiding the merge rule in the replacement of connected interior spaces. On the other hand, Tran et al. (2018) presents topological relations reconstructed among cuboid shapes by the grammar rules learned from the input point clouds that are to be used automatically and finally compensate for the missing points.

3. Method

Our method proposes a top-down hierarchical approach for the automatically segmentation and classification of indoor point clouds, taking advantage of the extraction of connectivity between entities for classification refinement towards an effective reconstruction of as-built buildings from point clouds.

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3.1. Data preprocessing

Data pre-processing aims to simplify the representation of three-dimensional data prior to more sophisticated analyses. The proposed method uses subsampling algorithms to reduce the size and density of the point cloud as well as contour extraction techniques to remove outdoor points. Although the removal of outdoor points is often an initial step in point cloud processing, it is not always necessary. In general, in buildings that have floorplans of different sizes and shapes, it is advisable to implement an outdoor point removal stage prior to storey segmentation.

The removal of outdoor points is based on DBSCAN and alpha shapes. First, the DBSCAN algorithm is applied to the point cloud of a storey. At this stage only points belonging to the largest cluster detected by DBSCAN are retained. Points from smaller clusters are discarded together with the points labelled as noise by DBSCAN. The density criterion is defined through two parameters, namely *eps*, which is the maximum distance between two points for being considered neighbours, and *min_samples*, which is the minimum number of neighbours a point must have to belong to a cluster (instead of being considered noise).

Then we extract the storey contour by creating a 3D alpha shape of the largest cluster returned by DBSCAN. The alpha shape associated with a set of points is a generalization of the concept of convex hull. Alpha shapes are strongly influenced by parameter α, as an alpha shape has an edge between two members of the point set whenever there exists a generalized disk of radius $1/\alpha$ containing none of the point set and the two points lie on its boundary. The second stage of outdoor points removal is completed by filtering out those points that are outside the alpha shape.

3.2 Storey segmentation

As previously mentioned, our top-down approach starts by segmenting the building point cloud by storeys, from which a topological connectivity graph is automatically derived. On one hand, subdividing original point clouds into smaller datasets enhances the computational efficiency of subsequent processing. On the other hand, the extraction of connectivity is fundamental for the complete representation of the building as a topological graph representing relationships between entities and spaces.

Given that buildings are typically composed of horizontally levelled storeys, many authors already explored the partition of the point cloud into storeys by analysing the frequency of Z values (Khoshelham & Díaz-Vilariño, 2014). Our method is also following this assumption. Accordingly, a histogram is calculated considering as parameter the number of bins, *n*, which is determined from a knowledge-based adjustment considering the nature of the data. For example, in the case of residential buildings, Scott's rule can be successfully applied to determine an optimal bin width and hence the number of bins in the histogram. This rule uses standard deviation and the number of observations in the data set as parameters. The rule formula indicates that the *bin width (h)* is calculated as 3.5 times the standard deviation of the data, divided by the cube root of the number of observations. This approach seeks to find a balance between smoothing the representation of the distribution and highlighting meaningful patterns.

Next, the average of the frequencies of the Z-histogram is calculated and the peaks are identified. The highest k Z-frequencies of the histogram are selected depending on the number of plants *num_s*. For example, in the case of 2 storeys, the 4 highest frequencies of the histogram are selected; similarly, for 3 storeys, the 6 highest frequencies are selected. In general, the number of histogram peaks to be detected is twice the number of plants, i.e. $k = num\_s * 2$.

Figure 1 shows an example of a three-storey building segmentation. The left-most peak represents the floor of the lower storey. This placement ensures the incorporation of all floor points into the storey during segmentation. The same reasoning applies to the higher storey placed at the right-most side of the histogram. The transition between the ceiling of one storey and the floor of the storey above is represented in figure 3 by red lines in the middle of the corresponding pair of histogram peaks.

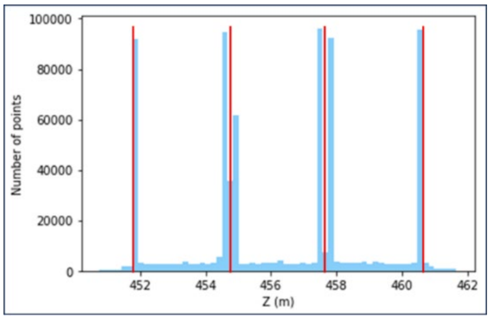

Figure 1. Histogram of Z coordinates of the point cloud of a three-storey building.

Although the precise connection of storeys may be obtained from the location of stairs and elevators, a simple topological graph can be already derived from the storey-segmentation results (Figure 2).

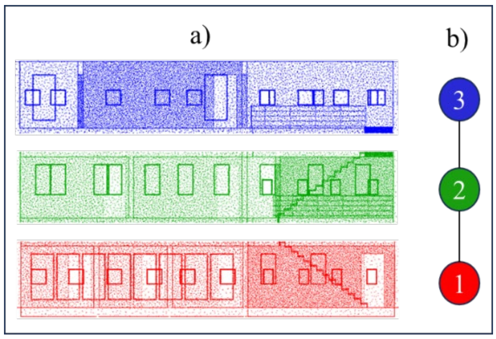

Figure 2. a) Point cloud segmentation by storeys, b) inter-storey connectivity graph.

3.3. Room segmentation

Room segmentation is performed following a 3D mathematical approach (Balado et al, 2020, Frías et al, 2020). Instead of using the point cloud itself, this approach is based on analysing the empty space of a building indoor, whose definition is more robust than wall segments, especially in case of low-quality point clouds.

Our approach follows a classical morphological opening applied to a voxel structure. As the structuring element is also a cube of side *l*, the indoor point cloud is initially oriented such that its main axes are aligned with the coordinate axes (x, y, z). Afterwards, the point cloud is voxelized, with voxels classified

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as *occupied* if they contain points, *indoor empty* if they do not contain points and are inside the building contour, and *outdoor empty* if they do not contain points and are outside the building contour. *Indoor empty* voxels are the ones selected for further processing. The voxel resolution should be carefully determined to ensure that the empty space within inner walls is not misrepresented by empty voxels.

The room segmentation process involves erosion, individualization, dilation and point cloud classification. As previously mentioned, we use a 3D structuring element, modelled as a cube whose side *l* is determined based on the width of the doors. Erosion is performed to break the continuity of the empty indoor space through doors. Then, each room is individualized by using a 3D connected components algorithm.

The parameter *connectivity* indicates the type of connectivity considered between the voxels. Using a connectivity of 26 indicates that connections could be in all directions. The output is a labelled voxel structure where each component has its own unique label, providing an individualized representation of rooms in three-dimensional space. Next, dilation is applied using the same structuring element, a cube with side *l*. Finally, *occupied voxels* are further classified based on proximity to individualized clusters. Following this process, the initial point cloud is segmented in rooms (Figure 3).

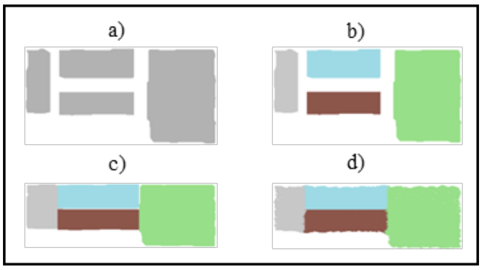

Figure 3. a) Erosion, b) Individualization, c) Dilation, d) Point cloud classification.

The result of the described process is shown in Figure 4.a. The inter-room connection, Figure 4.b, is extracted after door detection following the approach presented by (Frías et al, 2020). This approach uses the continuity of the indoor space -*indoor empty voxels*- between adjacent rooms to detect open doors connecting rooms.

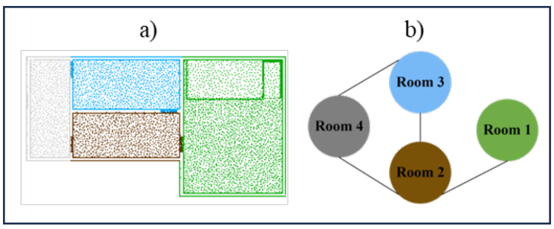

Figure 4. a) Rooms, b) inter-room connectivity graph.

3.4. Envelope segmentation

The next stage of the proposed processing pipeline is floor and ceiling segmentation. The candidates to be floor or ceiling are identified by estimating normal in the point cloud. This approach selects points which normal have a Z component greater than an adjustable threshold between 0 and 1, where a value closer to 1 indicates an interest in detecting horizontal planes. The RANSAC algorithm is applied separately to the lower and upper parts of the point cloud of the storey in order to obtain the planes that best fit the floor and ceiling, respectively.

Walls are detected by iteratively applying the RANSAC algorithm to the vertical planes, i.e. the points whose horizontal component of the normal vector is close to 0. Each time a new plane is fitted, its neighbouring points are discarded so that in the next iteration the RANSAC algorithm is applied only to the remaining points. The adjacency between pairs of detected walls can be established from the room segmentation results (see section 3.3).

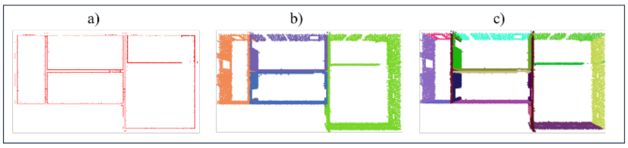

Figure 5. a) All walls, b) walls by room, c) walls in each room.

For the segmentation to yield correct results, only the points corresponding to building elements must be fed to the classification algorithm, discarding the points corresponding to objects inside the rooms. This filtering operation can be performed by retaining only the points that are within a threshold distance from the convex hull of the walls. If a room has columns or objects located close to the walls, an additional refinement step is necessary.

Since the lines formed on the point clouds tend to extend infinitely, an observation is made to determine if these lines are parallel or intersect. If they intersect, the angle of intersection is calculated and, if the angle is very small, the centroids of the point clouds involved are calculated. It is then determined whether these centroids are very close to each other, in which case only the largest point cloud is retained. On the other hand, if the lines turn out to be parallel, the distance between them is evaluated, and if it is less than a certain *threshold*, the largest point cloud is selected for subsequent analysis.

To determine if two walls of the same room are adjacent, the following process is carried out: first, the intersection point of the lines that represent the walls of the room and that were previously obtained is calculated. Next, it is checked if they are adjacent by creating an area around the intersection point defined by a previously established *radius*. Finally, it is analysed which of those points are inside and it indicates which walls are adjacent. To determine if two walls of different rooms are parallel, the following procedure is employed.

To determine the adjacency between two walls belonging to different rooms, the following procedure is used. Initially, the centroid of one of the walls is calculated. Subsequently, an orthogonal projection of said centroid is made on the plane of the other wall. The distance between the centroid and the projected point of the other wall is calculated. If this distance is less than a predefined *threshold*, the walls are established as adjacent. Figure 6 shows this method.

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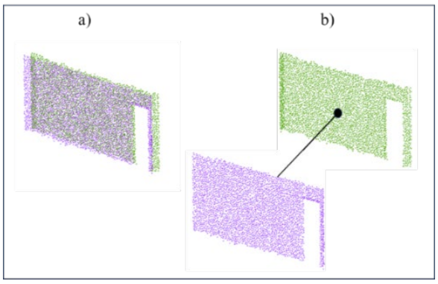

Figure 6. a) Two parallel walls of different rooms, b) how calculated distance between centroids of walls.

The intra-room adjacency of each wall can be seen in the Figure 7. The black dotted lines denote the adjacency between walls inside each room, while the red dotted lines denote the adjacency between walls belonging to different rooms.

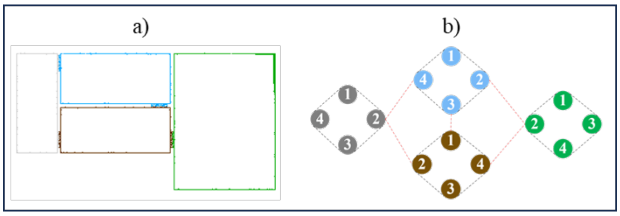

Figure 7. a) Walls in rooms, b) inter / intra-room adjacency graph.

4. Experiments and Results

4.1. Case studies

Case study 1 corresponds to a one-storey building composed of several rooms connected by one corridor, while case study 2 is a two-storey indoor scene containing multiple rooms. Figures 9 and 10 show the input data, which a size of 43.919.562 points and 1.918.295 points respectively.

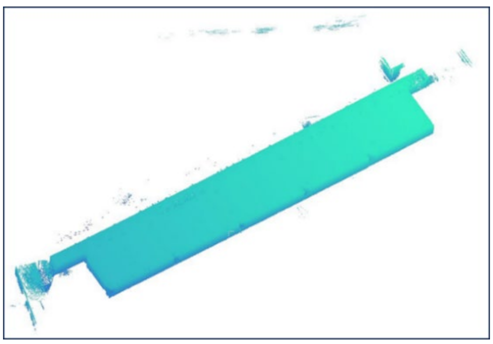

Figure 9. Figure of the case study 1.

4.2. Experiments and results for case study 1

The process starts with voxelization, applying a resolution of 0.1 determined by the width between walls. Then a DBSCAN algorithm is applied for storey cleaning. For this case the values of *eps*, which corresponds with the maximum distance between two samples and of *min_samples*, which is the minimum neighbourhood size, are 0.3 m and 2 respectively. This process together with the contour extraction utilizing an *alpha value* of 3.2 that implies a stricter connection between neighbouring voxels, yields the result in Figure 11.

Figure 10. Case study 2: a two-storey building with multiple rooms.

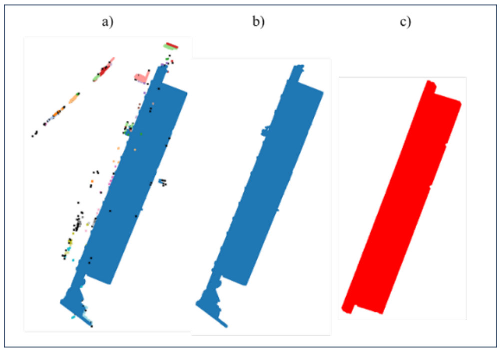

Figure 11. a) Initial point cloud, b) clean point cloud, c) contour extraction.

In this case, segmentation by storeys will not be applied since there is only one storey. Now, the room segmentation process starts and voxels are classified as *occupied, indoor empty* and *outdoor empty*. A structuring element based in width of doors is used with a length of 11. The results of breaking the continuity of empty indoor voxels are shown in Figure 12.a) with 3D erosion. Then 3D connected components is applied using a *connectivity of 26* that indicates that connections could be in all directions which is shown in Figure 12.b). After all of this, a dilation is applied with the same *structuring element* and its result is illustrated in Figure 12.c). Finally, *classification of occupied voxels* based on proximity to individualized clusters will result in the segmentation of the initial point cloud into rooms, as shown in Figure 12.d).

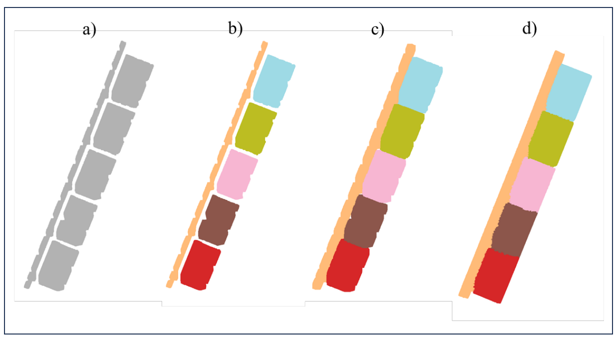

Figure 12. a) Erosion, b) Individualization, c) Dilation, d) Point cloud classification

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For detecting walls, a vertical plane and RANSAC algorithm are used and the selected threshold to adjust planes is 0.05. Walls can be viewed separately in each room. In this case rooms are not complete rectangular due to the presence of occlusions such as projectors or lockers located in the corners. Figure 13 shows the adjacency between rooms and walls in each room that is represented by black lines and black dotted lines, respectively. Red dotted lines represent the adjacency between parallel walls of different rooms.

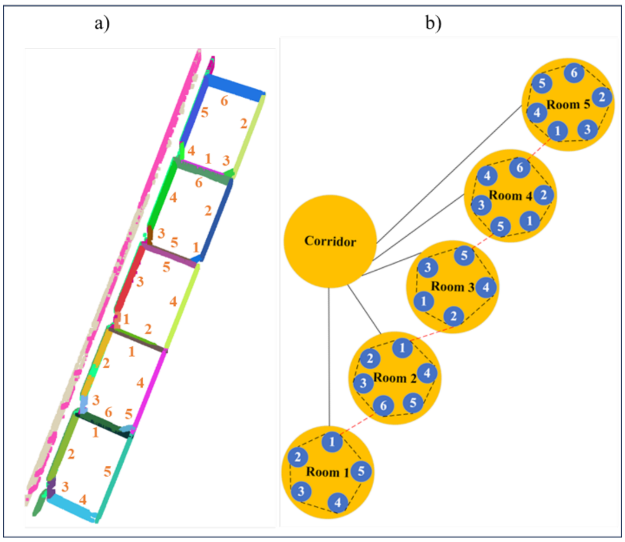

Figure 13. a) Walls, b) topological relation graph.

Currently, detailed information on room adjacency has been obtained, but the analysis of hallways has not yet been completed. For this reason, adjacency between room walls and hallways is not represented.

4.3. Experiments and results for case study 2

The segmentation by storeys has been done using a histogram with Scott's rule, requiring only a parameter for the number of storeys, which in this case is 2. As a result, the point cloud has been divided into two storeys.

Before proceeding with room segmentation in a storey, it is essential to carry out voxelization preprocessing step, utilizing a voxel size of 0.1 m and a contour extraction using an *alpha value* of 3.2. Once this step is completed, room segmentation process as shown in Figure 14 is executed. First, these voxels are classified as *occupied*, *indoor empty* and *outdoor empty*. A *structuring element* based in width of doors is used with a length of 7.

Results of break the continuity of empty indoor voxels are shown in Figure 14.a) with 3D erosion. Then 3D connected components is applied using a *connectivity of 26* that indicates that connections could be in all directions, which is shown in Figure 14.b). After all of this, a dilation is applied with the same *structuring element* and its result is illustrated in Figure 14.c). Finally, *classification of occupied voxels* based on proximity to individualized clusters will make that the initial point cloud is segmented by rooms.

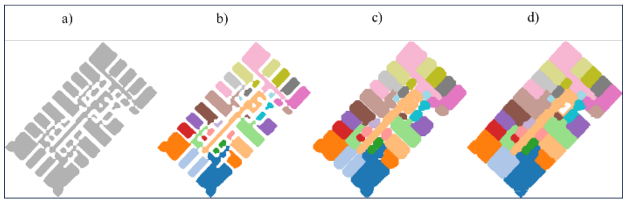

Figure 14. a) Erosion, b) Individualization, c) Dilation, d) Point cloud classification.

For room segmentation, the *voxel resolution* is important as it is chosen to ensure that the empty space of the interior wall is not represented by empty voxels. In this case there are interior walls with different sizes, so the room segmentation contains some errors. This can be solved by selecting the rooms with incorrect segmentation and changing its *voxel size* parameter. The selected value is 0.05, and the same process is repeated accordingly. Figure 15 shows how the rooms that were not correctly segmented are now correctly segmented.

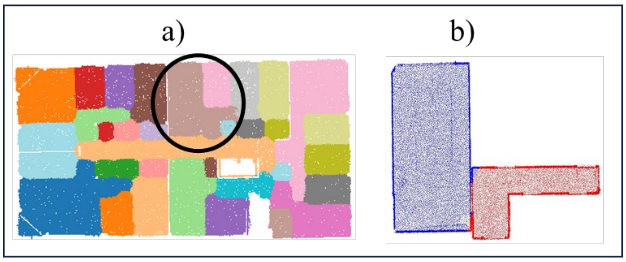

Figure 15. a) Segmentation with errors, b) segmentation after repeating the process.

The same procedure as before is employed to detect walls, which can be viewed all together, by rooms, and within each room individually, as shown in Figure 16.

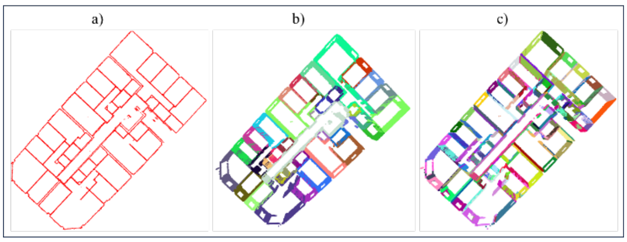

Figure 16. a) All walls, b) walls for room, c) walls in each room.

The presence of some errors in room segmentation means that wall segmentation is not completely accurate, which causes points that should be in one room to be in another adjacent room as illustrated in Figure 17.

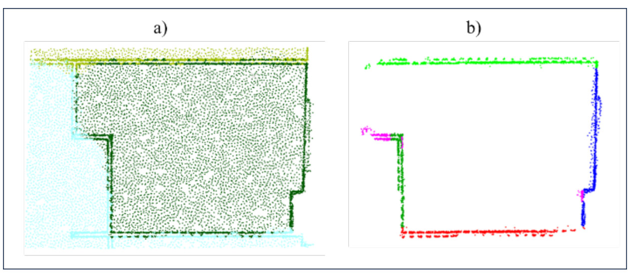

Figure 17. a) Room with errors, b) walls in room with errors.

Due to the large number of rooms, the relationship between the walls of the rooms corresponding to rooms 35 and 36 is shown in Figure 18. Black lines and black dotes lines represent adjacency between rooms and walls in each room, respectively. Red dotes lines represent adjacency between parallel walls of different rooms. Furthermore, due to the limited number of points or small room sizes, wall segmentation is not performed accurately in these cases.

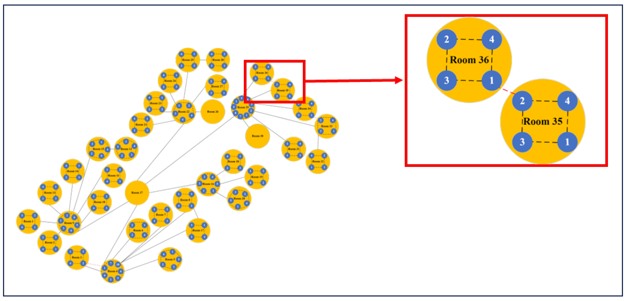

Figure 18. Topological relation graph between walls.

5. Conclusions

In this paper a top-down hierarchical approach for indoor segmentation and topology-graph retrieval is presented. This approach simplifies and improves the accuracy of room and element segmentation by progressively reducing the complexity of the building structures to be analysed. This strategy is demonstrated to be effective for the segmentation of MW building layouts, but non-MW could be addressed by implementing an isotropic structuring element, what would be considered for future work. Next steps will also explore the use of these topological graphs to building reconstruction, and special attention will be given to the reconstruction elements such as columns, beams, windows, or staircases.

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