

AUTOMATION OF AS-BUILT BIM CREATION FROM POINT CLOUD: AN OVERVIEW OF RESEARCH WORKS FOCUSED ON INDOOR ENVIRONMENT

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ABSTRACT:

While BIM (Building Information Modelling) appears as a solution to reduce the cost and environmental impact of buildings, its implementation on existing buildings is still a major challenge. In the last five years, an important number of publications on the topic have been published. This paper proposes an up-to-date overview about the automation of as-built BIM creation from point clouds, focused on indoor environment. It is structured in two main parts. The first one deals with the segmentation and classification of point clouds by storey, rooms, walls, and slabs. The second one focuses on the modelling, strictly speaking, of the main elements of an indoor scene. The approaches are grouped into principal ideas. Through the presentation of methods using new types of scanners and associated sensors, it highlights the promising use of other information in addition to 3D geometry.

1. CONTEXT AND INTRODUCTION

It has been about ten years since “BIM” (Building Information Modelling) made in the AEC industry vocabulary. Its aim is to store and centralize building data through 3D digital representation of building components with semantic information. Facility managers work usually with paper documents and plans which are not systematically up to date. With the use of BIM, it is estimated that the time to search information could be reduced by 83% and 5% of operating costs per year could be saved (Zeiss, 2018). Being aware that 75% of total building lifecycle costs would concern the operating phase, the use of BIM represents an important cost saving for facility managers and owners. Coupled with the promise of reducing the environmental impact of buildings, its use is pushed worldwide by governments. This increasing interest is illustrated by the growing number of publications on the subject (Figure 1).

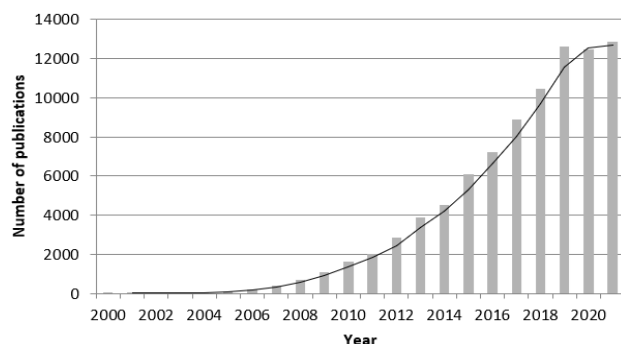


Figure 1. Number of publications with the keywords ‘Building Information Model(ing)’ each year, in Google Scholar

When the BIM is set up from the beginning of a construction project, it is called “as-designed BIM”. It is the ideal situation because all elements are known, modelled, and semantically completed, even hidden objects. However, the model must be updated throughout all the building’s lifecycle. Unfortunately, it is rarely done. For existing buildings, the BIM must be established from collected data and is called “as-built BIM”.

To capture data, traditional surveying techniques like tacheometers and handheld laser distance meter are largely replaced by laserscanning techniques. Terrestrial Static Laser Scanners (SLS) provide ever faster point clouds which are geometrically more exhaustive compared to traditional techniques. More recently, Mobile Laser Scanners (MLS) enable even more flexibility in the acquisition (fast and easy) at the expense of density and noise. While photogrammetry is largely widespread in outdoor environments for façade survey for instance, it is more unusual for surveying indoor environments. This is mainly due to the challenge to use such a technique. Photogrammetric indoor acquisitions require a large number of overlapping images and tie points. Therefore, as-built BIM modelling is largely based on the processing of point clouds provided by direct 3D measuring sensors like SLS or MLS. Despite fast improvements in terms of acquisition, modelling is still a laborious task, mainly done manually. It is extremely time consuming and error prone. Even skilled modellers might produce significantly different models, as highlighted by Esfahani *et al.* (2021).

In this context, this paper presents an overview of research projects carried out in the field of automatic scan-to-BIM over the past ten years. It focuses on indoor environments of buildings. A first section deals with the segmentation and classification of point clouds. Then, for each of the mainly studied building components, the approaches retained by a large community are summarized. Lastly, the outcomes of the reviewed methods are discussed.

2. INDOOR POINT CLOUD SEGMENTATION AND CLASSIFICATION

This first part deals with the segmentation and classification of point clouds. Like typical interior spaces, it is organized in a hierarchical manner with the storeys, rooms and structural elements like walls, floors, and ceilings. Figure 2 presents the most common segmentation workflow followed by authors in automatic scan-to-BIM approaches. Every step will be described in the next paragraphs.

2.1 Processing multi-storey buildings

Many approaches presented in the literature deal with the processing of data acquired in multi-storey buildings. Although some research teams process multi-storey simultaneously, most of them focus on dividing the input data into individual storeys. Two approaches are often suggested for this purpose: a) ones exploit the distribution of points along the vertical axis and b) others use the scanner trajectory during data capture.

The most common solutions are based on density histograms along the vertical axis. When the point cloud distribution along the vertical axis is analysed, it is assumed that floors and ceilings are horizontal. The values for which the histogram frequencies are high correspond to the floor and ceiling heights in the cloud. They are used for example by Xiao et al. (2012) to divide the input point cloud into horizontal slices. Histograms used in this manner do not consider floors or ceilings with level differences. Macher et al. (2017) and Pexman et al. (2021) seek to overcome this issue. Indeed, Macher et al. (2017) apply this histogram analysis to each scan station to associate them a ground and ceiling height. The points of all stations are then gathered according to these values to form point clouds of each storey. Pexman et al. (2021) apply Z-histogram analysis to the entire building point cloud. Horizontal slices are extracted for each peak and transformed into binary images. Smallest pixel areas are considered as outliers because they most likely correspond to furniture. The overlap between areas in neighbouring peaks images is then measured to combine them like mosaics. The authors obtain images for each floor and ceiling describing their height distribution. The point clouds of each storey correspond to the points in the height intervals given by the floors and ceilings images.

Nikooheemat et al. (2018) propose a very different method, relying on the trajectory acquired by dynamic scanners. The trajectory is divided into horizontal or inclined segments. Segments with similar angles and with less than two meters height difference are gathered. The points corresponding to the different storeys are selected thanks to timestamp.

2.2 Segmentation in rooms

Once the point cloud is segmented into storeys, a segmentation into rooms is generally carried out. Most of the methods assume that walls are vertical. Methods based only on point cloud mainly rely on the gaps formed by walls in the point clouds. Those using dynamic scanners data, exploit the acquisition trajectory in addition.

Armeni et al. (2016) consider buildings following a Manhattan-World scheme, i.e., following a cartesian system with walls, floors and ceilings perpendicular to each other. This enables them to search for gaps with density histograms along the two main horizontal axes of buildings, regarding for "peak-gap-peak" patterns. Although this method is robust in cluttered environments, the Manhattan-World assumption is very restrictive. Many authors overcome this assumption by projecting storeys' point clouds in a horizontal plane, to form a binary image. The aim is then to detect pixels clusters which are separated by voids. While the continuity in the point clouds is preserved at doors, the challenge becomes to separate image areas. Macher et al. (2017) avoid this problem by projecting only a slice of the point cloud close to the ceiling and thus above the doors. Bormann et al. (2016) through the presentation of several methods, first propose the use of morphological operators to separate connected areas. The occupied areas, i.e.,

where points were projected into the pixels, are eroded iteratively. Surface area thresholds (number of pixels) are used to check if the zones are separated. In this case, they are set aside and labelled as rooms. The pixels in the original image, which have been eroded, are in turn labelled, from near to far, with a wavefront. In a very similar way, Bormann et al. (2016) propose to consider for each accessible pixel the distance to the nearest edge. Applying a threshold on the distance values allows to separate central areas (with maximum distances) and then, with a wavefront, to find all the rooms. The third method suggested by the same authors relies on a Voronoi diagram, giving the image's skeleton. The first two methods are more sensitive to room clutter and tend to gather corridors with adjacent rooms. The third method sometimes divides the corridors into multiple rooms. Based on these findings, Jung et al. (2017) propose a method that is less sensitive. The areas are separated by considering pixels located at a distance from the edge, slightly larger than the width of a door. On the empty pixels surrounding these areas (walls) a skeletonization algorithm is used to define the approximate axis pixels. The accessible pixels are labelled from these watertight skeletons surrounding the rooms. All these methods, based on a 2D segmentation, produce rooms point clouds by considering projected points forming each 2D room areas. In 3D, Frias et al. (2020) suggest a transposition of the methods using morphological operators on a grid of voxels.

When considering the acquisition of the trajectory of mobile systems, Diaz-Vilarino et al. (2017) and Zheng et al. (2018) search for doors. The aim is to cut the trajectory at each door crossing. Then, the point cloud is divided into segments regarding the points' timestamp. The former rely on the fact that the height of the doors is lower than the ceiling height. In the profile of the ceiling, along the path, the doorway corresponds to the points with a low average height. Zheng et al. (2018) work in 3D with dynamic scanner scanlines and then in 2D, to define door opening segments. The scanlines are segmented into linear primitives and their geometry allows to detect holes in planes. These lines form candidate doors segments. Since the doors are vertical, the candidates close to each other in 2D correspond to the same opening. The approach of Diaz-Vilarino et al. (2017) is completed to merge subspaces belonging to the same room. This phenomenon appears when a room is crossed several times. The problem is solved with an energy function minimization. The function involves two terms computed, in subspaces, with a ray tracing from the trajectory. The data term evaluates whether the subspace represents a room in its entirety, while the smoothness term measures the ability of different subspaces to complement each other.

2.3 Walls and slabs segmentation

Buildings are mainly composed of planes. That is why the authors all agree on a segmentation step of the point clouds into planes. Generally, this step is followed by a classification. While these steps are mostly focused on the detection of main structural elements, some authors exploit knowledges about these ones and steer their search so that the classification is performed at the same time as the segmentation.

To detect points on walls and slabs, some authors exploit their position and their normal to limit the search for planes. For example, Tran et al. (2020) simply limit their plane search for points on horizontal or vertical surfaces with respect to their normal. Such methods are restrictive because furniture are also made of horizontal and vertical planes.

Thus, for the segmentation of slabs, many authors exploit in addition the distribution of points along the vertical axis. While Valero et al. (2012), Diaz-Vilarino et al. (2017), Jung et al. (2018) or Cui et al. (2019) settle for it, Macher et al. (2017) add a robust estimator. In a different way, for ceilings, Ambrus et al. (2017), keep points with the highest elevation in a storey point cloud decomposed into vertical cells. Planes searches are performed on these points. They do the same for floors by searching for points with lowest height values.

For walls, the hypothesis of verticality is systematically made. Under this assumption, some authors even look for lines rather than planes. Thus, to define room boundaries, Oesau et al. (2014), Li et al. (2018) and Jung et al. (2018), for example, rely on images of point cloud projected with no floor nor ceiling. Jung et al. (2018) consider pixels and their associated points as part of a vertical surface, when points are within a range near the ceiling. These points are grouped into straight lines with a Douglas-Peucker algorithm. Li et al. (2018) use an iterative region growing algorithm that groups points with a similar normal and close to each other. By projecting the ceiling, Valero et al. (2012) and Macher et al. (2017) can search for area contours rather than lines. Macher et al. (2017) extract room contours with a region growing algorithm during the segmentation of a storey into rooms. In all these cases, at this stage, the authors provide contour pixels of the rooms. In order to fit line segments, Macher et al. (2017), Li et al. (2018) and Jung et al. (2018) use least squares algorithms. Li et al. (2018) apply an Iteratively Reweighted Least Squares (IRLS) algorithm. It is an M-estimator weighting points based on their squared distances. Macher et al. (2017) choose Maximum Likelihood Estimation SAmple Consensus MLESAC. It corresponds to an improvement of the RANSAC estimator, by evaluating the quality of the consensus points set with the likelihood measure. Jung et al. (2018) add parallelism constraints. In a similar way, Oesau et al. (2014) and Valero et al. (2012) use a Hough transform to recognize lines in images. Finally, the method of Diaz-Vilarino et al. (2017), unlike the others, considers a point density image. The authors do not look for contours nor points forming lines, but for pixels grouping a large quantity of points and corresponding to vertical surfaces. This can be compared to the analysis of distribution histograms conducted simultaneously on the X and Y axes. While for most of these authors, wall detection is limited to these steps, Diaz-Vilarino et al. (2017) and Macher et al. (2017) use their isolated points or their contours to steer the search for vertical planar segments. More simply, Valero et al. (2012) consider all the points set along these extruded sides at the height of the rooms.

Without steering the segmentation by assumptions on the targeted elements, the segmentation is performed directly with robust estimators and region growing algorithms.

The RANdom SAmple Consensus RANSAC algorithm is widely used. Points forming planes within a certain tolerance to the average plane are isolated as planar segments. This distance threshold depends on the data noise and on the thickness of the objects to detect. In a similar manner, Macher et al. (2017) choose MLESAC. Without additional concerns, planar segments isolated in this way may contain several groups of non-contiguous points. Thomson et al. (2015) introduce a criterion based on the Euclidean distance between groups. This is similar to the application of region growing algorithms as done by Previtali et al. (2018) and Shi et al. (2019). The latter, however, consider in addition, a similar normal criterion, allowing to eliminate also points in recesses.

Nikooheemat et al. (2018) as well as Bassier et al. (2020) adopt methods based solely on region growing algorithms. Region growing algorithms applied on point clouds, can take different

criteria to extend their regions. The most common methods consider only geometric ones: proximity, normal, and distance to a local plane. Bassier et al. (2020) include point colour as an additional criterion for clustering them. However, the light conditions can limit its use.

All these methods undoubtedly lead to an over-segmentation. So, Previtali et al. (2018), Nikooheemat et al. (2018) or Cui et al. (2019) complete the process by merging planar segments according to coplanarity, orientation and distance criteria. Bassier et al. (2020) transpose the topology between planar segments into a graph and apply a Conditional Random Field algorithm to cluster them.

When the planar segmentation is not steered to find specific elements, a classification is performed. Since authors are mainly looking for structural elements, they eliminate planar segments that are too small or do not support enough points. This step is based on local and global features of the planar segments. Local features can be evaluated for each occurrence, in particular their orientation, their centroid, or their extent. The global features concern the neighbouring of the planar segments and are measured in pairs. For example, the relative position of centroids, the angle formed between two of them, their overlap or their proximity are global features. According to the hypotheses, more or less constraints and features are used.

For example, Thomson et al. (2015) extract vertical and horizontal planar segments and only interpret them based on their orientation. Without other constraints, planes belonging to furniture are not eliminated. Global features are introduced to distinguish them from others. Previtali et al. (2018) thus classify horizontal planes as floors or ceilings when they are also the lowest, respectively the highest, surfaces in the point cloud of a storey. For planar segments of walls, they are looking for those on the edges of the rooms. Mura et al. (2014) and Murali et al. (2017) add an extent criterion since they only keep those whose vertical extent is close to the room height. To avoid eliminating too many planar segments due to occlusion, Mura et al. (2014) control the presence of masks from the scan stations and artificially fill in the planar segments in hidden areas.

Nikooheemat et al. (2018), Bassier et al. (2020), and Mura et al. (2016) differ by avoiding the strict assumptions of horizontality and verticality for classification. They introduce more contextual relations organized in a graph. Nikooheemat et al. (2018) and Mura et al. (2016) conduct their classification on heuristic considerations of architectural rules. Based on transition rules, Mura et al. (2016) search for paths in the graph between ceilings and floors, first, and then between walls. Bassier et al. (2020) use a random forest classifier.

To finish with segmentation and classification, deep-learning (DL) approaches are currently being increasingly developed in that way. Even if they have been adopted for a long time in the field of image processing, DL approaches are only emerging in the field of point cloud processing. For instance, Karama et al. (2021) implement *Mask R-CNN* into a cubic image. One of the first solutions directly applied on point cloud was suggested by Qi et al. (2017), developing *PointNet++*.

In summary, point cloud segmentation is an essential step before proceeding to modeling. First, the indoor point cloud is segmented into storeys, generally followed by a segmentation into rooms. The two main approaches, overcoming the Manhattan-world scheme, seek doors crossing with MLS data or use occupancy images, in a more general way. Planar segments are detected in a final step. They constitute the starting elements for modelling which is detailed in the next section.

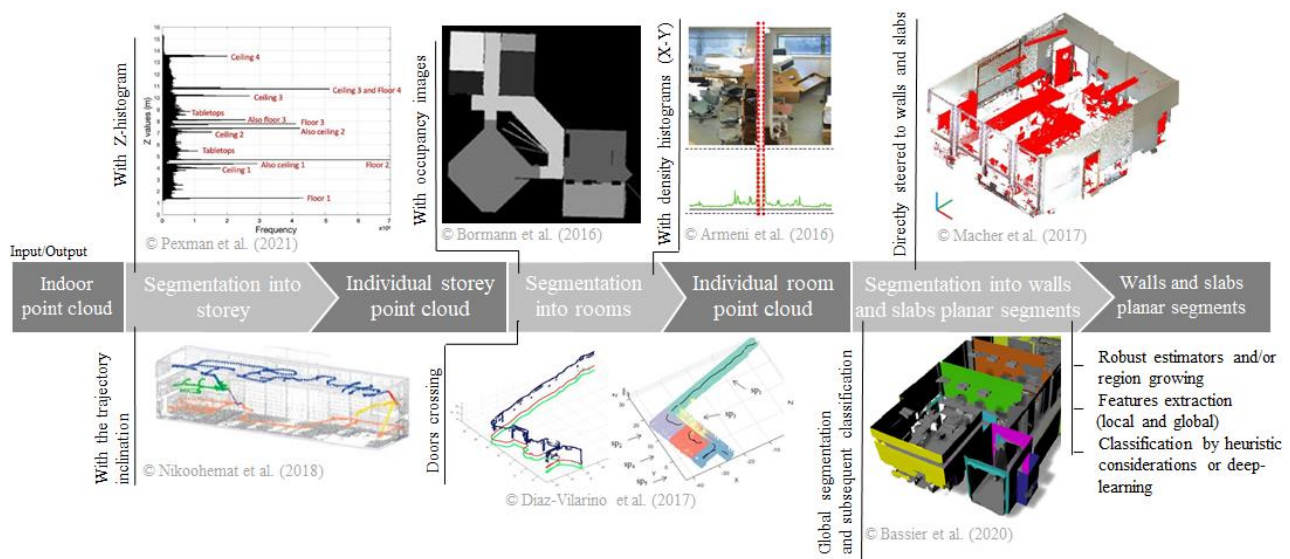


Figure 2. Main segmentation workflow followed by authors in automatic scan-to-BIM approaches

3. AUTOMATIC AS-BUILT BIM MODELLING

Once the point clouds are classified, the modelling is conducted. The approaches developed for the modelling of the rooms, openings and stairs are developed in this section.

3.1 Rooms modelling

To model the rooms, two approaches are opposed. The first one aims at modelling the rooms free space while the second one focuses on solid surfaces, like walls (Figure 3).

3.1.1 Free space based modelling: Most of approaches considering the free space modelling are based on cells partitioning. To achieve this decomposition, Budroni et al. (2010) make the strict architectural assumption of a scene following a Manhattan-World scheme. They rely on histograms looking for peaks to detect important planes in the three main directions. Without making this very strict hypothesis, all the authors assume vertical walls. Cells are, in general, created by the intersection of 2D lines corresponding to the projection of the wall faces on a horizontal plane. For those starting from planar segments and not from 2D lines, robust estimators or algorithms based on least squares are used to fit them. Yang et al. (2019) differ in their line construction by considering curves in addition to straight lines. The lines, which are then redundant, are clustered. The authors group only the near-collinear straight lines, around the longest of them, averaging their orientation. Wang et al. (2017), and Mura et al. (2014) do the same with a 1D mean-shift. Oesau et al. (2014) assuming that the load-bearing wall pattern is shared across storeys, use lines sets defined on all of them to partition their space. Finally, Mura et al. (2016) and Tran et al. (2020) divide the spaces into 3D cells by directly intersecting the planes of the structural elements. Turner et al. (2014) propose for their part a triangular cells decomposition. Their vertices are pixel centres of those with the higher density value in the image of the projected point cloud.

Except Murali et al. (2017) who classify the interfaces, the cells are further classified into free spaces (or rooms) and solids (walls and, sometimes, slabs). The aim is to deduce free spaces cuboids. To perform cells classifications, Budroni et al. (2010) and Li et al. (2018) focus on the presence of points within cells when the occupancy image of the storey point cloud is superimposed. Turner et al. (2014) classify first their triangular

cells with rays from scan stations. The internal cells are then grouped by room by minimizing the length of the interfaces between groups (rooms), i.e., by minimizing the width of the doors. Other authors mainly rely on the presence of points on the interfaces. It reflects for them the presence of a wall. Xiao et al. (2012) and Tran et al. (2020) exploit this single criterion for their classification testing for several models by classifying/declassifying the cells to choose the one that best fits the point cloud. Tran et al. (2020) use the reversible jump Markov Chain Monte Carlo (rjMCMC) algorithm which simulates random walks in a set of models. With a completely different manner, Mura et al. (2014) implement a diffusion map coupled with a k-medoids algorithm to group the cells into rooms (Figure 3). On such a map, the smaller the "diffusion distance" between two cells is, the more likely the cells belong in the same room. It is built from the number of points on the interfaces. Finally, a last but very common approach involves the minimization of an energy function. This is conducted in graphs, with cells as nodes and interfaces as links. Functions are based on two terms. The data term relies to the nodes, reflecting their probability of belonging to a given class. The smoothness term is attached to the relationships between nodes. The authors using this technique differ from each other in the way they calculate their terms and the chosen resolution algorithm. The consideration of points on faces is a constant for this second term evaluation. Regarding the data term calculation, Oesau et al. (2014) involve a ray tracing from cells to measure the number of intersections with structural elements. Wang et al. (2017), from successive scanner positions, measure the proportion of rays passing through the cells. A high proportion reflects a high probability to belong to free space. The others authors classify the cells into rooms. Yang et al. (2019) evaluate the data term with the projection in the cells of a point cloud classified into rooms. Mura et al. (2016), compare for each cell, their visibility areas on structural elements against those of each scan station whose room label is known at this stage. Ambrus et al. (2017) define their data term to group cells visible from the same viewpoint by comparing the points in cells to those visible from each viewpoint. To end, the authors use various algorithms to conduct the minimization of these energy functions. Graph-cuts of Boykov and α - β algorithms are mainly used. Wang et al. (2017) complement this classification into internal or external cells, grouping them by rooms, similarly to Mura et al. (2014), since "diffusion times" between cells and diffusion trees are involved.

Once the room's free space is identified, a parametric model of the space distribution can be deduced. It is generally made up of a set of watertight planes. The room hull is the merge of identically classified cells. When the classified cells are in 2D, the height of the rooms is defined by the one of the floors and ceilings planar segments (§ 2.3). Xiao et al. (2012) are additionally interested in walls and slabs volume. The authors, who applied their classification on 2D cells in a set of horizontal slices, deduce a rooms' 3D model by extruding and combining them over the heights of each slice and across all horizontal slices. To deduce the volume of walls and slabs, they use mathematical morphology operators. So, they inflate the model of the rooms and subtract the original model.

Some authors do not consider these steps of partitioning and classification. They directly define the hull of each room by intersecting parametric planes fitted to the wall planar segments. This is the approach followed by Velero et al. (2012), Diaz-Vilarino et al. (2017) and Shi et al. (2019). Mura et al. (2014) is at the interface between the two approaches. In one hand, they conduct a space partitioning and classify the resulting cells. Nevertheless, in another hand, the purpose of this classification is to find walls planar segments to form the rooms hulls.

3.1.2 Walls and slabs based modelling: Approaches looking for the modelling of walls and slabs face those addressed so far. Once the planar segments of walls and slabs have been isolated, the aim for the authors following this approach is to parametrically reconstruct these elements. The authors first agree on clustering planar segments of each wall. This clustering is generally based on simple contextual features. Thus, Thomson et al. (2015), Macher et al. (2017) or Nikoohemat et al. (2020) proceed in this way by using parallelism and distance criteria (Figure 3). Jung et al. (2018) apply the same principle in 2D to associate lines. Bassier et al. (2020) process with a Conditional Random Field (CFR) algorithm. It is applied after a coarser grouping, aiming to eliminate impossible combinations. The combinations are evaluated in a graph in which the planar segments are nodes. Links are broken based on several distance thresholds and other empirical criteria. For example, links should not intersect with other planar segments of walls or room contours.

These groups are the basis for parametric reconstruction of walls and slabs objects. Almost all the authors make the vertical walls and constant thickness assumption. They are therefore looking for their axis, their height and their thickness. Bassier et al. (2020) give a detailed method proceeding for each group of planar segments (Figure 3). The thickness of objects is calculated as the average orthogonal distance between the faces. Authors exploiting only indoor data as input usually assign an arbitrary thickness to the outer walls. Macher et al. (2017) prefer to isolate such objects and parameterize them by planes. For the wall axis Bassier et al. (2020) define a centreline with RANSAC. The vertical extent is defined by grouping the planar segments of floors and ceilings into average levels. Thomson et al. (2015) indicate calculating the contour of slabs with the convex hull of planar segments.

At this stage, these objects are not necessarily connected to each other. They correspond to their visible parts in point clouds. While Thomson et al. (2015) and Macher et al. (2017) do not address the issue, the others offer several approaches in this way. For Jung et al. (2018), this is referred to as a grammar-based approach. Junctions are constrained from the step of walls parameterization by the search for orthogonal lines. This method lacks flexibility. Similar to what is done for searching

rooms rather than walls, Previtali et al. (2018) pass through a cells decomposition. Cells are defined by the intersection of wall segments projected in the horizontal plane with temporary lines drawn orthogonal to their limits of occlusion. Their classification as internal or external cells allows the authors to complete their walls. These methods contrast with those of Nikoohemat et al. (2020) and Bassier et al. (2020), proposing the intersection of the closest objects, without any orthogonality constraint a priori. It is referred to as connection-based methods. More flexible compared to a grammar-based approach, it also strongly reduces the number of candidates compared to a cells decomposition. Bassier et al (2020) go beyond a simple extension and propose several types of connections: by extending walls, orthogonal or mixed.

Finally, Ochmann et al. (2019) present a hybrid method of the two approaches presented above. The authors consider the point cloud of the building as a whole. They proceed to a clustering of planar segments for each structural element. When dealing with topology, the authors process to 3D cells decomposition of the space by the intersection of all planar segments. The problem is then to assign a label to each cell: a room, a wall or a slab.

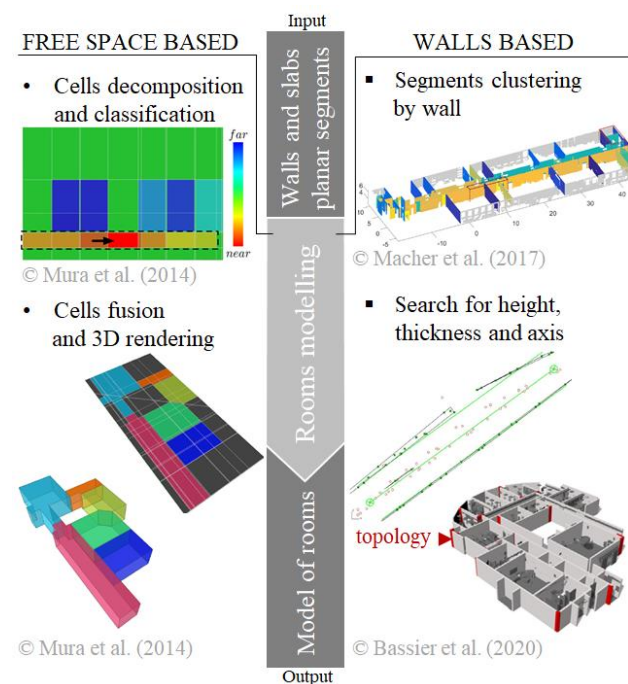


Figure 3. Main rooms modelling workflows: (left) rooms based and (right) walls based.

3.2 Openings detection

After the reconstruction of rooms, the detection and modelling of openings (windows and doors) is also a largely studied topic. All authors at this stage, know the geometry of the supporting walls, i.e., either parametric planes or point clouds of the walls. They also converge on the assumption of rectangular openings. Methods are grouped here regarding the information considered by the authors (Figure 4).

From the geometry solely, a common method consists in searching holes in walls. Many authors base their search on occupancy images of walls' points. The aim is to detect unoccupied pixels forming rectangular zones (Ambrus et al., 2017, Jung et al., 2018 and Yang et al., 2019). Other methods

are based on the detection of points located in the bounding boxes defined by the parallel planes of the walls. Pexman et al. (2021) use histograms, along vertical and walls axis, to detect openings and to deduce their dimensions. Finally, as Budroni et al. (2010) or Cui et al. (2019), other authors work on horizontal sections in which gaps in points coordinates along wall axis give the position and width of openings. The main issues with the sole geometry of the point cloud come from clutters which mask walls and openings parts. Moreover, the geometric features of openings are often slightly similar to the wall they belong to, especially when a door is closed. This makes it difficult to rely on simple geometric assumptions.

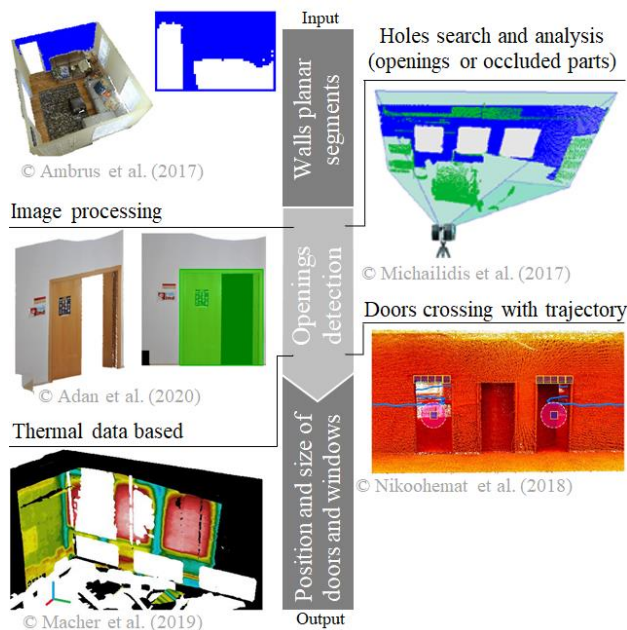


Figure 4. Main methods used for openings detection

Following these observations, authors brought in the successive scanner position data in their reasoning. Michailidis et al. (2017) and Nikoohemat et al. (2018) use them to detect hidden areas on walls (Figure 4). Rays are defined from each point of view to the measured points. If a ray passes through the considered wall, i.e., points have been measured behind it, then an opening is considered at the intersection. If a ray is stopped before the wall, i.e., it encounters points, then the area in shadow is a hidden area from this viewpoint. In addition, Nikoohemat et al. (2018) also consider the intersection of the trajectory with the walls as crossed doors. This consideration allows detecting doors which were closed in the point cloud but crossed during the acquisition (Figure 4). However, it only gives an approximate position of the doors in the walls, and only those crossed are detected. The context of determination of evacuation strategies allows such approximation.

In 2D, Wang et al. (2017) use a criterion similar to that of the trajectory/wall intersection. Their way to project point cloud has the particularity to consider points voxel by voxel from bottom to top to preserve the door openings. The basic assumption is that gaps corresponding to open doors are wider than those created by a lack of data and narrower than the width of a corridor. In a Delaunay triangulation based on the image contour points, triangles with sides whose length can correspond to a door size are filtered with the acquisition path.

Another common approach to detect openings relies on image processing. Adan et al. (2020) exploit colour and depth orthoimages of walls (Figure 4). They are looking for straight

lines, corresponding to discontinuities. Rectangle candidates defined by pairs of horizontal and vertical lines are analysed to retain those corresponding to real openings based on their size. Finally, considering that laser scanners also acquire Red Green Blue data (RGB), some authors study the contribution of radiometric information. As the RGB and intensity data are strongly correlated, they are studied separately by Macher et al. (2017). The authors attempt to separate the points with distinct intensity returns. They use an intensity frequency histogram cluster the points around peak values. With RGB data, they conduct a supervised classification approach based on maximum likelihood. The following problems are raised: a) the same object can have different colours b) the intensity values have the drawback of not being absolute, from one scanner to another and depend on the range and the incidence angle. Finally, more recently, the interest of thermal data for the detection of openings is raising (Macher et al., 2019) (Figure 4).

3.3 Stairs

The modelling of stairs is currently little discussed. It is raised a bit, mostly by research teams interested in the field of robotic and indoor navigation. Sanchez et al. (2012) and Nikoohemat et al. (2020) address this in the case where the point cloud of the stairwell is isolated. Floor and ceiling are known with described methods for modelling the rooms.

The authors start by detecting the points of the staircase ramps, by searching for inclined planes, in the point cloud. Sanchez et al. (2012) use RANSAC with some constraints regarding the inclination and extent. Nikoohemat et al. (2020) apply a region growing algorithm to group close near to near points. In both cases, the authors use a distance threshold to the searched plane necessarily wider than for the wall search above (e.g. 20 cm) to conserve all the points corresponding to the steps.

Then, from the points on each ramp, they model the staircase that best fit them. Sanchez et al. (2012) infer the ramp orientation, step width, and an insertion point from its smallest rectangular bounding box. A vertical section, oriented along the axis of the ramp, on which horizontal and vertical lines are adjusted, allows them to detect the start and end points of each rise and tread of a step. The number of steps as well as their average height and depth are deduced. To detect steps, Nikoohemat et al. (2020), on the other hand, apply again a region growing algorithm, but with a finer threshold than before. Plane point clouds are obtained for each rise and tread of steps. The parametric modelling is then based on a graph in which the nodes are the point clouds of rises and treads. If two of them are adjacent and create a perpendicular angle, they are connected to each other. The longest path in the graph corresponds to the steps of the staircase. The number of nodes divided by two gives the number of steps and the average size of the steps is deduced from the smallest enclosing rectangles of each node.

In summary, rooms modelling methods can be grouped into those focused on walls and those focused on free spaces. The following openings detection relies on the analysis of holes in walls planar segments. Finally, the topic of stairs modeling is very little addressed and generally limited to straight stairs.

4. RESULTS AGAINST BIM SPECIFICATIONS

Even though scan-to-BIM algorithms are constantly being developed and improved, there is still a gap between most of the results obtained with the reviewed automatic methods and the BIM specifications. BIM is much more than just a simple 3D

model. It is organised as a structured file format in which building components are separated in hierarchical objects (site, building, level, walls, windows, doors, furniture, etc.). With the need to collaborate on BIM, the IFC (Industry Foundation Classes) format was born. It is an open exchange standard format for defining building elements. Only a few approaches stand from the others by proposing as a result a model in IFC format or in a BIM proprietary format. Among the studies referenced here, only Thomson et al. (2015), Macher et al. (2017), Tran et al. (2018) and Bassier et al. (2020) deals with this issue. It can be noticed that the authors who consider the walls often best meet the BIM specifications. The others provide as output some CAD files with 2D lines, or a set of planar patches or volumes.

5. CONCLUSION

This paper gives an overview of the automatic scan-to-BIM approaches proposed in the literature and focused on indoor environments. The segmentation of the point cloud is the first step. The methods used are clearly conditioned to the choice of input data, the type of objects of interest and architectural assumptions. Segmentation constitutes the basis for the modelling. Rooms, openings and stairs are the main elements composing an indoor building and therefore their segmentation and modelling are largely discussed in the literature. Their proper modelling is essential before the search for other objects because these elements form the basis of every indoor environment.

The paper highlights the links and the differences between the approaches. The authors differ greatly in their assumptions and in the input data. More or less strict assumptions are made about the architecture of buildings, particularly about walls and slabs orientation. Moreover, while some research teams choose to focus exclusively on point cloud geometry, others go against and exploit additional information. The former explains their choice by the fact that additional information are not always available depending on the used scanning system and thus their method would be more universal. On the contrary, the latter take advantage of scan positions or trajectory, for instance. This is often a way of transposing methods based on SLS data to MLS. Furthermore, these data or radiometric ones (intensity, color, or even infrared thermal data) are increasingly available since sensors are often an integral part of the device. The aim is also to exploit every possibility of such acquisition technique. These differences are also due to the fact that teams working on the subject have various backgrounds. Some of them are rather geomaticians and try to reproduce as accurately as possible the scene. Others belong to the field of robotics and their purpose is the localization in a building. To finish, the authors use different data sets with various characteristics to evaluate their results. The considered environment is more or less cluttered and complex, and different sensors are used. All these choices make difficult the comparison of approaches. It has led Khoshelham et al. (2018) to propose a benchmark.

Our future work will focus on exploiting additional data like trajectory or thermal data for completing the automation of scan-to-BIM processes. Simultaneously, a methodology allowing to assign a quality criterion to the modelled elements will be investigated.

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