IFC WALL RECONSTRUCTION FROM UNSTRUCTURED POINT CLOUDS

M. Bassier,* Ralf Klein, B. Van Genechten and M. Vergauwen

Dept. of Civil Engineering, TC Construction - Geomatics
KU Leuven - Faculty of Engineering Technology
Ghent, Belgium
(maarten.bassier, ralf.klein, bjorn.vangenechten, maarten.vergauwen)@kuleuven.be

Commission II/WG4

KEY WORDS: Building Information Modeling, Reconstruction, Wall, Building Point Clouds

ABSTRACT:

The automated reconstruction of Building Information Modeling (BIM) objects from point cloud data is still ongoing research. A key aspect is the creation of accurate wall geometry as it forms the basis for further reconstruction of objects in a BIM. After segmenting and classifying the initial point cloud, the labelled segments are processed and the wall topology is reconstructed. However, the preocedure is challenging due to noise, occlusions and the complexity of the input data.
In this work, a method is presented to automatically reconstruct consistent wall geometry from point clouds. More specifically, the use of room information is proposed to aid the wall topology creation. First, a set of partial walls is constructed based on classified planar primitives. Next, the rooms are identified using the retrieved wall information along with the floors and ceilings. The wall topology is computed by the intersection of the partial walls conditioned on the room information. The final wall geometry is defined by creating IfcWallStandardCase objects conform the IFC4 standard. The result is a set of walls according to the as-built conditions of a building. The experiments prove that the used method is a reliable framework for wall reconstruction from unstructured point cloud data. Also, the implementation of room information reduces the rate of false positives for the wall topology. Given the walls, ceilings and floors, 94% of the rooms is correctly identified. A key advantage of the proposed method is that it deals with complex rooms and is not bound to single storeys.

1. INTRODUCTION

The creation of as-built Building Information Modeling (BIM) models is a widely researched topic. These models reflect the state of the building up to as-built conditions and are used for quality control, quantity take-offs, maintenance and project planning (Volk et al., 2014, Patraucean et al., 2015). An as-built model is obtained by updating an existing as-design model of the structure or by reverse engineering it from measurements taken on the site. This research focusses on the creation of a BIM without a prior model since few buildings currently have a model. A key aspect in the reconstruction is the modeling of the wall geometry as it forms the basis for other objects. Currently, these objects are created by manually designing them based on point cloud data acquired from the built structure. However, this process is labour intensive and error prone.

Automated reconstruction approaches focus on the unsupervised processing of point clouds. The interpretation of this data is challenging due to the number of points, noise and the complexity of the structure (Tang et al., 2010). Also, most point clouds are acquired with remote sensing techniques which are bound to Line-of-Sight (LoS). As a result, crucial parts of the structure are occluded due to clutter or inaccessible areas. Reconstruction algorithms make assumptions about these zones which are prone to misinterpretation.

The emphasis of this work is on the reconstruction of walls from large unstructured point clouds of buildings. More specifically, we look to create wall objects that are both accurate and have consistent topology. The proposed method is able to properly reconstruct and connect wall geometry even in highly cluttered and noisy environments. Also, our approach operates directly on the 3D point cloud itself and is designed for multi-storey buildings.

The remainder of this work is structured as follows. The background and related work is presented in Section 2. In Section 3. the methodology is presented. The test design and experimental results are proposed in Section 4. Finally, the conclusions are presented in Section 6.

2. BACKGROUND & RELATED WORK

The automated procedure of creating BIM objects from point cloud data commonly consists of the following steps (Nguyen and Le, 2013). First, the data is preprocessed for efficiency. In 2D methods, the point cloud is represented as a set of raster images consisting of a slice of the data or other information (Landrieu et al., 2017, Anagnostopoulos et al., 2016). In 3D methods, the point cloud is restructured as a voxel octree which allows efficient neighbourhood searches (Vo et al., 2015). After the preprocessing, the data is segmented. A set of primitives is detected that replaces the point representation with the purpose of data reduction. Typically, lines are used in 2D methods and planes or cylinders are used in 3D methods (Vo et al., 2015, Lin et al., 2015, Fan et al., 2017, Vosselman and Rottensteiner, 2017). Next, the segments are classified by reasoning frameworks exploiting local and contextual information. Class labels such as floors and walls are computed for each segment by using heuristics or machine learning techniques (Bassier et al., 2016, Wolf et al., 2015, Xiong et al., 2013, Nikoohemat et al., 2017). The resulting labelled segments are used to extract the necessary parameters for class-specific reconstruction algorithms.

Several researchers have proposed methods for the reconstruction of wall geometry. Most approaches focus on the creation of wall

*Corresponding author

https://doi.org/10.5194/isprs-annals-IV-2-33-2018

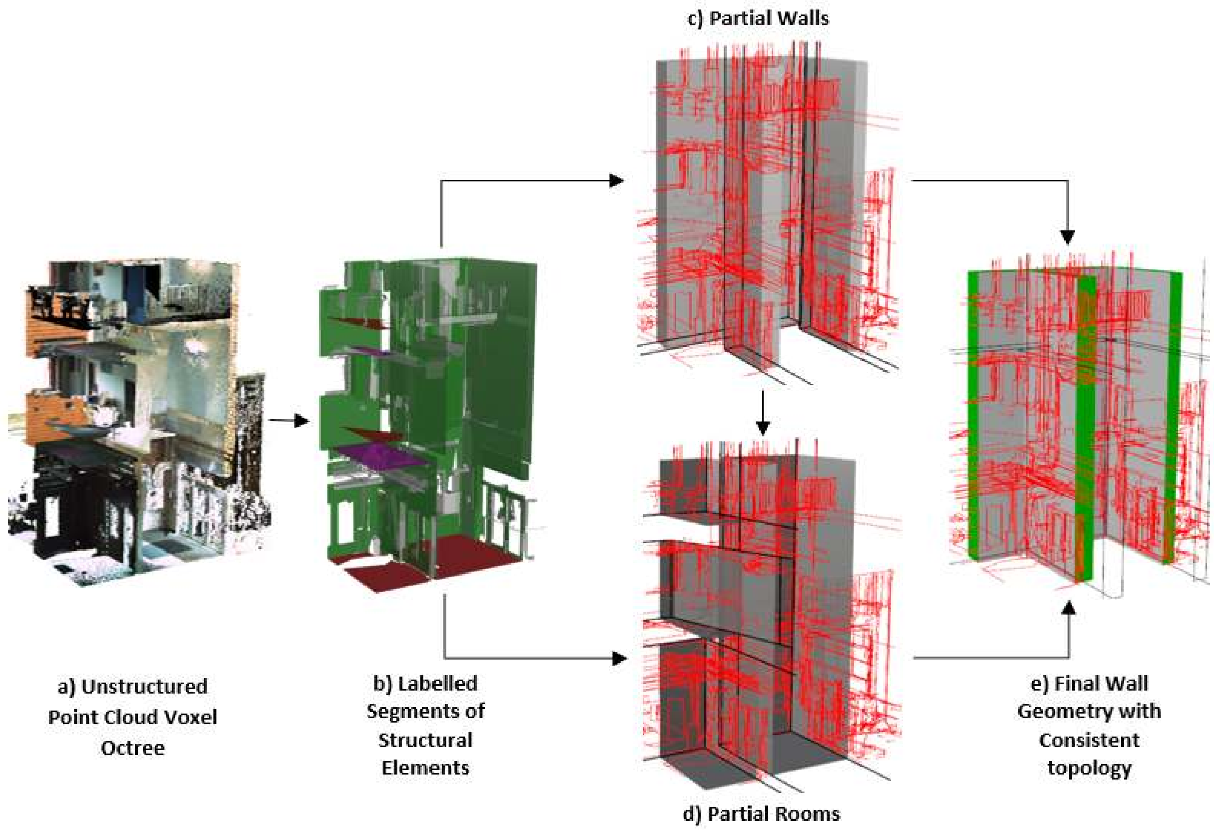

Figure 1: Overview general workflow wall reconstruction. Colorised point cloud (a), labelled planar primitives including walls, ceilings, floors, etc. (b), partial walls in grey and other geometry in red (c), partial rooms in grey and remaining geometry in red (d) and final walls in grey with green interior and remaining geometry in red (e).

surfaces opposed to actual BIM geometry. For instance, Xiong et al. and Adan et al. reconstruct planar wall boundaries and openings based on machine learning (Xiong et al., 2013, Adan and Huber, 2011). Michailidis et al. reconstruct severely occluded wall surfaces using a bayesian graph-cut optimization on a cell complex decomposition (Michailidis and Pajarola, 2016). We extend these approaches by clustering the wall segments and thus using both faces of a wall to extract the necessary parameters to accurately reconstruct volumetric BIM objects.

The reconstruction of rooms opposed to walls is also being researched. Typically the initial wall segments are used to create watertight room meshes. For instance, Oesau et al. consider the creation of watertight rooms as a 2D graph-cut optimization problem (Oesau et al., 2014). Budroni et al. and Previtali et al. use line intersections in a 2D cell decomposition (Budroni and Böhm, 2010, Previtali et al., 2014). Similar to our approach, they combine both ceiling and floor geometry to create initial blue prints for the rooms. Valero et al. solves the intersections of pre-segmented wall lines to create a closed area (Valero et al., 2012). In this research, the wall intersections are performed in 3D and aided by the volumetric room representations which can deal with more complex zones. Several 3D approaches also have been presented. For instance, Turner et al. proposed 3D voxel carving to create watertight meshes of rooms (Turner and Zakhor, 2014). They determine individual room labels by performing a min-cut on a 2D graph of the Delaunay mesh of the floor plan. They are one of the few researchers that perform a multi-storey reconstruction which also is the goal of this research. However, their emphasis is on room boundaries while this research focusses on accurate wall reconstruction.

Closely aligned with our work are the room reconstruction methods of Ochmann et al. (Ochmann et al., 2016) and Mura et al. (Mura et al., 2016, Mura et al., 2014). They both focus on finding the optimal room layout. Ochmann et al. considers room reconstruction as a 2D graph optimization problem based on intersecting candidate wall segments. After determining the room information, they fit wall objects on the rooms edges. Mura et al. does not reconstruct walls but computes the most likely set of 3D room representations based on a 3D graph of the wall, floor and ceiling segments. Both show very promising results for wall and room reconstruction. We distinguish ourselves from them by considering volumetric wall segments opposed to surfaces for the reconstruction. The best fit partial wall objects are very accurate and lower the number of candidate intersections. Also, our method focusses on multi-storey data sets.

3. METHODOLOGY

In this paper, a reconstruction algorithm is proposed that creates both accurate and consistent wall geometry. An overview of the general workflow is depicted in Fig. 1. First, the point cloud data is segmented (Fig. 1a) and semantically labelled (Fig. 1b). Next, the pre-segmented wall surfaces are clustered to create partial wall objects (Fig. 1c). In parallel, partial rooms are computed based on the nearby floor, ceiling and partial walls (Fig. 1d). Finally, the topology of the walls is computed given the intersections between the partial walls aided by the room information (Fig. 1e). The consecutive steps are discussed in detail in the following paragraphs.

Data Preprocessing Prior to the reconstruction, the data is segmented and classified. First, the unstructured point cloud is represented as a voxel octree (Fig. 1a) after which planar patches are

https://doi.org/10.5194/isprs-annals-IV-2-33-2018

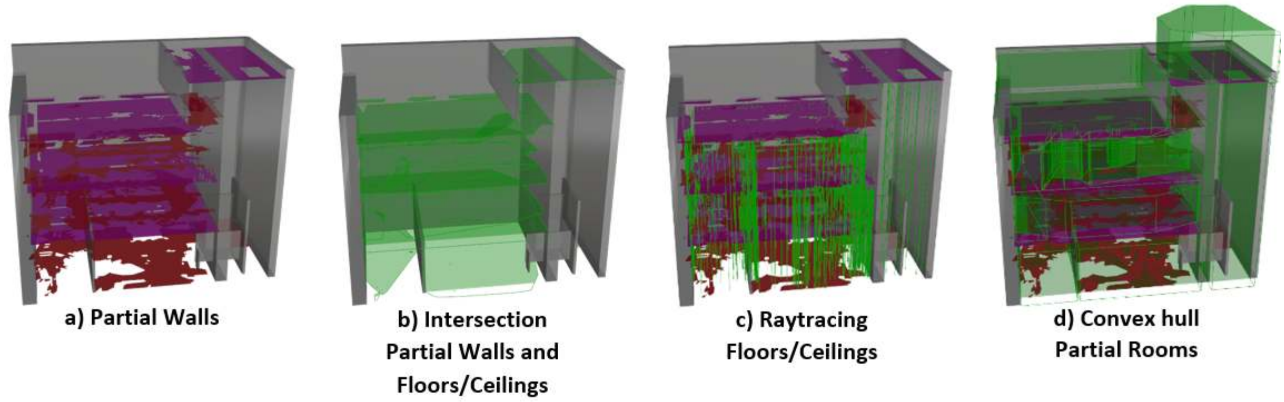

Figure 2: Overview workflow partial room reconstruction with partial walls in grey, floors in red and ceilings in purple: partial walls (a), adjusted floors/ceilings by intersection with partial walls (b), match between floors and overlaying ceilings trough ray-tracing (c) and convex hull of partial walls (d).

extracted from the data as presented in our previous research (Bassier et al., 2017a). Next, the planar patches are subjected to a reasoning framework that computes class labels for each patch. A pre-trained set of Support Vector Machines (SVM) is used for the classification (Bassier et al., 2017b). The result is a set of labelled segments that replaces the point cloud representation of the building (Fig. 1b).

Partial Wall Reconstruction The partial wall reconstruction consists of two consecutive steps. First, the individual wall segments are clustered using a heuristic reasoning framework. A graph $G(S, E)$ is defined with each node $s \in S$ a wall segment and each edge $e \in E$ a connection between neighbouring surfaces. The euclidean distance between the boundaries of the segments is used as the criterium for the adjacency matrix of G. Pairwise relations are computed for each edge including the paralellity, coplanarity, orthogonality, intersection of the edges with other surfaces and distance between boundaries. A majority vote based on heuristic thresholds is used as a graph cut to compute a set of clusters. The result is a set of associatively clustered walls segments.

The second step is the reconstruction of the partial walls themselves. In this research, IfcWallStandardCase objects are created conform the IFC4 standard (BuildingSMART International Ltd, 2013). This subtype of the IfcWall entity has access to the IfcMaterialLayerSet that defines the material layers in the wall, making it the preferred type in Scan-to-BIM workflows. Additionally, the parametric representation allows other entities to interact with the object such as door and window openings. However, there are geometric constraints to the IfcWallStandardCase such as verticality and uniform thickness. Given the clustered segments, the wall parameters including the orientation, location, boundary and thickness are extracted. A weighted approach is considered based on the area of each segment s to compute the best fit partial walls $w \in W$. All parameters are extracted from the 3D surface representation which ensures an accurate 3D reconstruction. The orientation of the wall object is given by computing the best fit centre plane $p(w)$ (Eq. 1).

$$p(w) = \begin{cases} c_w = \sum_{s \in w} \omega_s c_s \\ \vec{n_w} = \sum_{s \in w} \omega_s \vec{n_s} \end{cases} \tag{1}$$

Where the wall orientation $\vec{n_w}$ and location c_w are based on each $s \in w$. The weights ω_S are based on the surface areas of s. As discussed above, each wall is computed with a uniform thickness. Given $p(w)$, the surfaces on both faces of each wall s_i, s_j are identified. Next, the best fit thickness d of w is given by the weighted average distance from s_i and s_j to $p(w)$ along $\vec{n_w}$ (Eq. 2).

$$d(p(w), s_i, s_j, \boldsymbol{\omega}) = \sum_{s \in s_i, s_j} \omega_s \frac{|ax_s + by_s + cz_s + d|}{\sqrt{a^2 + b^2 + c^2}} \tag{2}$$

where $p(w) : d = ax + by + cz$ and ω_s are the same as in the orientation. The wall boundary of the partial walls is given by the height between overlaying floors and the length of w in the XY plane. The result is set of best fit partial wall objects with a uniform thickness (Fig. 2a).

Room Reconstruction The room reconstruction is based on the floors, ceilings and partial wall objects. Three consecutive steps are defined for the room reconstruction (Fig. 2). First, the partial wall objects W are used to segment the floors and ceilings (Fig. 2b). The nearby w of each floor s_f and ceiling surface s_c are identified based on the distance between boundaries. The floors and ceilings are segmented by solving the physical intersection between s_f, s_c and W. The portions of s_f and s_c that lie within W are removed. Also, the segmented surfaces are filtered by size to avoid small parts of ceilings or floors to contribute to the reconstruction.

Once the data is segmented, the floors and ceilings belonging to each other are determined. A raytracing algorithm is proposed that computes which floors and ceiling are directly overlayed (Fig. 2c). For each triangle t in s_f, a semi-infinite vertical ray $l(\vec{x}) = \vec{z}x + t(\vec{c})$ is constructed that contains the centroid $t(c)$ of t. Candidate ceilings for s_f are found by the intersection between $l(\vec{x})$ and the s_c above. The candidates of s_f are conditioned to include only the first intersection of each ray. Also, only candidate s_c are withheld when having sufficient overlap with the source s_f based on a threshold. s_f and s_c with no inliers are given an offset up to the height of their nearest counterpart. Once s_f and s_c are paired, their combined surface area is used to compute the volumetric convex hull (Fig. 2d). the result is a set of volumetric partial rooms.

Wall Topology The topology of the walls is computed based on the intersections of the partial walls aided by the room information. The centre plane of each partial wall is tested for intersections with other nearby partial walls (Fig. 3a). The euclidean

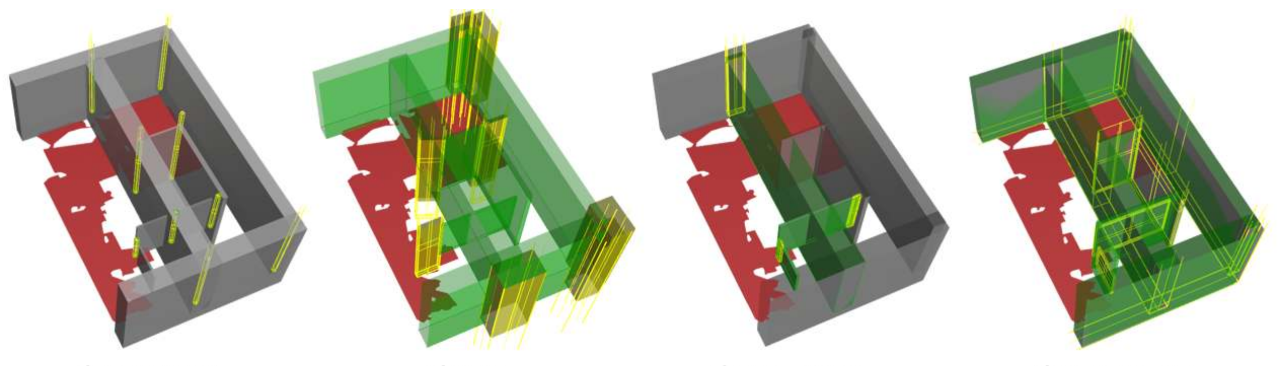

Figure 3: Overview workflow wall topology with partial walls in grey, floors in red, affected walls in green and changes in yellow: Intersections partial walls (a), trim overextend walls (b), extend walls horizontally (c) and extend walls vertically (d).

Table 1: Properties Multi-storey School Facility

Properties	Multi-storey building
Points	$\pm 500 Million$
Pre-segmented surfaces	7000
Wall segments	258
Floor segments	59
Ceiling segments	60
Reconstruction Time $[s]$	9.1s
Points $\in$ LOA20 $(0.05m)$	49%
Points $\in [95\%]$	0.22m

Table 2: Results of intermediate steps

Category	Ground Truth	Recall $[\%]$	Precision $[\%]$
Partial Walls	11	91	100
Partial Rooms	16	94	94
Wall Topology	14	100	100

distance between the boundaries of the partial walls is used a criterium for the neighbourhood search. Two types of connections are defined: The intersection of two non-parallel walls and the orthogonal connection between two near parallel walls. A connection is valid when meeting the following conditions. The average distance from the boundary of both partial walls to the intersection should fall within a threshold. Also, the intersecting walls should be approximately orthogonal or parallel (Eq. 3).

$$\theta_{\parallel} \leq \vec{n_{pw1}} \cdot \vec{n_{pw2}} \leq \theta_{\perp} \tag{3}$$

where $\theta_{\parallel}$ and $\theta_{\perp}$ are the thresholds for respectively the parallelism and orthogonality. Additionally, candidate intersections may not extend walls so they collide with the partial rooms. Once the intersections are determined, the final wall objects are created by updating the partial wall objects given their new dimensions. First, the partial walls that are overextended up to a threshold are trimmed to match the centre plane of the intersecting wall (Fig. 3b). Next, the walls with valid intersection points are extended along there centre plane in horizontal direction (Fig. 3c). The height of the walls is determined by the height of the closest overlaying and underlaying floor (Fig. 3d). The result is a set of walls with consistent topology that accurately reflect the as-built conditions of the Building Information Model (BIM).

The final step is to convert the geometry to actual BIM objects. In this research, the IFC4 protocol is used since it is compatible with most software. As previously stated, instances of the IfcWallStandardCase class are created to have access to the extensive parameter set provided for this class (BuildingSMART International Ltd, 2013). However, these objects have geometric constraints such as verticality and uniform thickness. Therefore, an abstraction is made of the geometry of each wall to create the objects along the Z-direction with a uniform height and thickness. The result is a set of best fit generic parametric BIM objects that reflect the state of the building and have access to an extensive set of wall parameters.

Figure 4: Overview clutter and occlusions wall reconstruction.

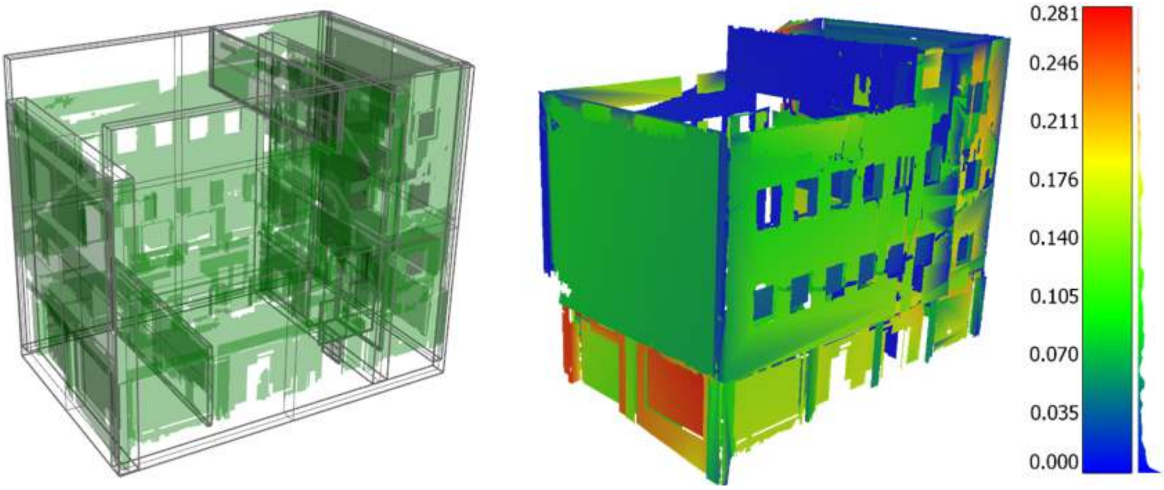

Figure 5: Overview Results wall reconstruction: The wall segments in green and the IfcStandardWallcase objects in grey (left) and the deviations between the model and the initial point cloud (right).

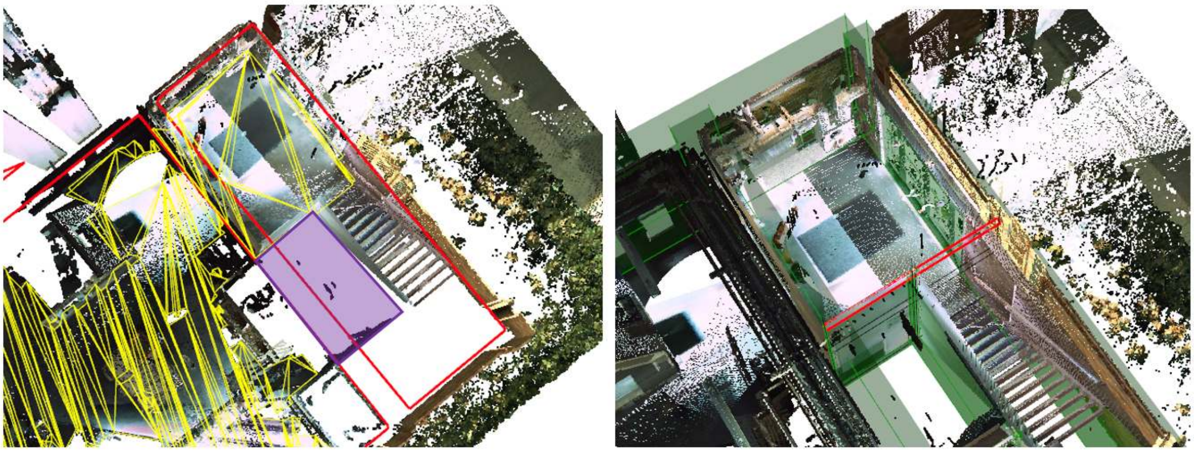

Figure 6: Overview partial room detection and wall topology: Failed room detection in purple due to absence floors and ceilings (left) and overextended wall in red that was rejected by room information (right).

4. EXPERIMENTS

The algorithm was tested on a multi-storey building on the Technology Campus in Ghent, Belgium. A total of 55 scans was acquired resulting in over half a billion 3D points (Table 1). The data was not de-noised and a wide variety of objects was present in the point clouds (Fig. 4). The algorithm was implemented Rhino Grasshopper (McNeel, 2015). The segmentation and classification were performed with algorithms developed in previous research (Bassier et al., 2017b, Bassier et al., 2017a).

The accuracy of the reconstructed BIM objects is tested against the initial point cloud which serves as ground truth (Fig. 5a). Table 1 and Fig. 5b show that the deviations between both data sets is 0.05m and 0.22m for respectively 49% and 95% of the data (U.S. Institute of Building Documentation, 2014). While the majority of the wall boundaries are accurate, substantial deviations are reported for complex walls with high detailing. This is mainly due to the abstractions that were made to create IFCStandardWallcase objects (BuildingSMART International Ltd, 2013). For instance, the bottom portion of the exterior walls shows increased errors due to an offset in the geometry. Additionally, several erroneous walls are present due to misclustering and failed intersections.

Table 2 reports the results of each step in the reconstruction process. For the comparison, 11 partial walls were defined as ground truth based on 258 pre-segmented wall segments. By default, the maximum wall thickness for the clustering was set to 0.7m with an angular threshold between segments of 15°. Over 90% of the wall segments were properly clustered save for a few smaller surfaces in complex scenarios. Next, the partial room detection was based on 59 floors and 60 ceilings surfaces. By default, the permitted overlap between overlaying ceilings for the raytracing of the floors was set to 20%. Several floor and ceiling surfaces did not have an overlaying or underlaying counterpart and were given an assumed extrusion height. The associative clustering of the partial room objects had a 94% recall and precision even though the scenes were highly cluttered and occluded. Fig. 6a reveals that zones that do not contain any floor or ceiling information are initially not detected. This is expected since our algorithm relies on this data for the reconstruction. For the wall topology, 14 intersections were defined as ground truth (Table 2). For the detection, the search radius for non-parallel walls was set to 2m while and for near-parallel walls it was set to 0.8m. Overall, all candidate intersections were found correctly due to the incorporation of the partial room geometry. The experiments show that crucial connections were rejected because of collisions with partial rooms (Fig. 6b).

https://doi.org/10.5194/isprs-annals-IV-2-33-2018 | © Authors 2018. CC BY 4.0 License.

5. DISCUSSION

Wall reconstruction is currently ongoing research. While most methods are capable of dealing with single-storey box-like rooms, there are few methods that deal with complex multi-storey zones. A key aspect is the formulation of the wall reconstruction as a 2D or a 3D optimization problem. In this research, it is stated that a 3D approach is preferred as it is more likely to be independent of horizontal floors, horizontal ceilings, vertical walls and consistent storeys. However, some assumptions are still made. Our approach relies for the initial detection of the rooms based on the presence of planar floors and ceilings. Therefore, a small percentage of the rooms will not be detected. However, the results show that the partial rooms have great potential to aid the wall topology without the need for extensive assumptions about occluded zones.

6. CONCLUSION

This paper presents an unsupervised method to reconstruct wall objects from unstructured point clouds of buildings. A 3D approach is proposed that deals with complex multi-storey data sets. First, partial walls are computed by associatively clustering presegmented planar wall segments. Next, partial rooms are defined by combining the floor,ceiling and wall geometry. The wall topology is created by computing wall intersections conditioned on the partial room objects. The final walls are created by defining IfcWallStandardCase objects for each object conform the IFC4 standard. The result of the method is a set of topologically consistent BIM walls that accurately reflect the as-built conditions of a building.

The experiments indicates that the used method is a promising reconstruction framework for unstructured point cloud data. Over 90 % recall and precision is reported for the clustering of the wall segments, the detection of the partial rooms and the reconstruction of the wall topology. When comparing to the initial point cloud, it is revealed that the majority of the wall boundaries are accurately reconstructed. However, there are major deviations near wall detailing due to the abstractions made to create IfcWallStandardCase objects. The results also prove that, by integrating room information in the reconstruction process, crucial false positives for the wall intersections are mitigated. Additionally, by operating in 3D, the method is independent of horizontal floors, ceilings and vertical walls. Overall, it is stated that the used algorithm shows promising results for wall reconstruction.

In future work, the presented approach will be investigated further to enhance the wall, room and topology detection. Also, the integration of wall detailing in IfcWallStandardCase objects is being researched along with wall opening detection. A similar approach will be implemented toward the creation of floor and ceiling objects.

7. ACKNOWLEDGEMENTS

The research group Geomatics of the Department of Civil Engineering, TC Construction at the KU Leuven in Belgium is gratefully acknowledged.

REFERENCES

Adan, A. and Huber, D., 2011. 3D Reconstruction of Interior Wall Surfaces under Occlusion and Clutter. *2011 International Conference on 3D Imaging, Modeling, Processing, Visualization and Transmission* pp. 275–281.

Anagnostopoulos, I., Patraucean, V., Brilakis, I. and Vela, P., 2016. Detection of walls, floors and ceilings in point cloud data. In: *Construction Research Congress 2016*.

Bassier, M., M, B., Van Genechten, B. and M, V., 2017a. Octree-Based Region Growing and Conditional Random Fields. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-2/W8, 2017 5th International Workshop LowCost 3D Sensors, Algorithms, Applications* XLII(November), pp. 28–29.

Bassier, M., Vergauwen, M. and Genechten, B. V., 2017b. Automated Classification of Heritage Buildings for As-Built BIM using Machine Learning Techniques. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* IV(September), pp. 25–30.

Bassier, M., Vergauwen, M. and Van Genechten, B., 2016. Automated Semantic Labelling of 3D Vector Models for Scan-to-BIM. *4th Annual International Conference on Architecture and Civil Engineering (ACE 2016)* pp. 93–100.

Budroni, A. and Böhm, J., 2010. Automatic 3d Modelling Of Indoor Manhattan-world Scenes From Laser Data. *ISPRS Commission V Mid-Term Symposium: Close Range Image Measurement Techniques* XXXVIII, pp. 115–120.

BuildingSMART International Ltd, 2013. Industry Foundation Classes Release 4 (IFC4).

Fan, Y., Wang, M., Geng, N., He, D., Chang, J. and Zhang, J. J., 2017. A self-adaptive segmentation method for a point cloud. *Visual Computer* pp. 1–15.

Landrieu, L., Mallet, C. and Weinmann, M., 2017. Comparison of belief propagation and graph-cut approaches for contextual classification of 3D lidar point cloud data. *IGARSS'2017*.

Lin, Y., Wang, C., Cheng, J., Chen, B., Jia, F., Chen, Z. and Li, J., 2015. Line segment extraction for large scale unorganized point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing* 102(March), pp. 172–183.

McNeel, R., 2015. Rhinoceros 5. Technical report.

Michailidis, G. T. and Pajarola, R., 2016. Bayesian graph-cut optimization for wall surfaces reconstruction in indoor environments. *Visual Computer* pp. 1–9.

Mura, C., Mattausch, O. and Pajarola, R., 2016. Piecewise-planar Reconstruction of Multi-room Interiors with Arbitrary Wall Arrangements. *Computer Graphics Forum* 35(7), pp. 179–188.

Mura, C., Mattausch, O., Jaspe Villanueva, A., Gobbetti, E. and Pajarola, R., 2014. Automatic room detection and reconstruction in cluttered indoor environments with complex room layouts. *Computers & Graphics* 44, pp. 20–32.

Nguyen, A. and Le, B., 2013. 3D Point Cloud Segmentation : A survey. *6th IEEE Conference on Robotics, Automation and Mechatronics* pp. 225–230.

Nikoohemat, S., Peter, M., Oude Elberink, S. and Vosselman, G., 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(September), pp. 355–362.

Ochmann, S., Vock, R., Wessel, R. and Klein, R., 2016. Automatic reconstruction of parametric building models from indoor point clouds. *Computers & Graphics* 54, pp. 94–103.

Oesau, S., Lafarge, F. and Alliez, P., 2014. Indoor scene reconstruction using feature sensitive primitive extraction and graph-cut. *ISPRS Journal of Photogrammetry and Remote Sensing* 90, pp. 68–82.

Patraucean, V., Armeni, I., Nahangi, M., Yeung, J., Brilakis, I. and Haas, C., 2015. State of research in automatic as-built modelling. *Advanced Engineering Informatics* 29, pp. 162–171.

Previtali, M., Barazzetti, L., Brumana, R. and Scaioni, M., 2014. Towards automatic indoor reconstruction of cluttered building rooms from point clouds. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences* II-5(June), pp. 281–288.

Tang, P., Huber, D., Akinci, B., Lipman, R. and Lytle, A., 2010. Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. *Automation in Construction* 19(7), pp. 829–843.

Turner, E. and Zakhor, A., 2014. Floor Plan Generation and Room Labeling of Indoor Environments from Laser Range Data. *GRAPP, International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications* pp. 1–12.

U.S. Institute of Building Documentation, 2014. *USIBD Level of Accuracy (LOA) Specification Guide. Document C120 [Guide] vers. 1.0*.

Valero, E., Adán, A. and Cerrada, C., 2012. Automatic method for building indoor boundary models from dense point clouds collected by laser scanners. *Sensors (Switzerland)* 12(12), pp. 16099–16115.

Vo, A. V., Truong-Hong, L., Laefer, D. F. and Bertolotto, M., 2015. Octree-based region growing for point cloud segmentation. *ISPRS Journal of Photogrammetry and Remote Sensing* 104, pp. 88–100.

Volk, R., Stengel, J. and Schultmann, F., 2014. Building Information Modeling (BIM) for existing buildings - Literature review and future needs. *Automation in Construction* 38, pp. 109–127.

Vosselman, G. and Rottensteiner, F., 2017. Contextual segment-based classification of airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing* ·.

Wolf, D., Prankl, J. and Vincze, M., 2015. Fast Semantic Segmentation of 3D Point Clouds using a Dense CRF with Learned Parameters. *IEEE International Conference on Robotics and Automation (ICRA)*.

Xiong, X., Adan, A., Akinci, B. and Huber, D., 2013. Automatic creation of semantically rich 3D building models from laser scanner data. *Automation in Construction* 31, pp. 325–337.