Detection of walls, floors and ceilings in point cloud data

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Abstract

The successful implementation of Building Information Models (BIMs) for facility management, maintenance and operation is highly dependent on the ability to generate such models for existing assets. Generating such BIMs typically requires laser scanning to acquire point clouds and significant post-processing to register the clouds, replace the points with BIM objects, assign semantic relationships and add any additional properties, such as materials. Several research efforts have attempted to reduce the post-processing manual effort by classifying the structural elements and clutter in isolated rooms. They have not however examined the complexity of a whole building. In this paper, we propose a robust framework that can automatically process the point cloud of an entire building, possibly with multiple floors, and classify the points belonging to floors, walls and ceilings. We first extract the planar surfaces by segmenting the point cloud, and then we use contextual reasoning, such as height, orientation, relation to other objects, and local statistics like point density in order to classify them into objects. Experiments were conducted on a registered point cloud of an office building. The results indicated that almost all of the walls and floors/ceilings were correctly clustered in the point cloud.

Keywords: BIM, as-is modelling, RANSAC, classification, point clouds

1. Introduction

The creation of an as-is Building Information Model (BIM) of a facility is a complex process, starting with the acquisition of the point clouds, which is followed by the accurate creation of surfaces and the inclusion of information regarding the objects, such as materials and .costs However, modelers spend an excess amount of time into clustering the points that correspond to each object prior to modelling them. This process is time and cost-prohibitive restricting asset-owners from using BIMs in their small scale projects.

To address this issue, we propose a novel algorithm which aims at detecting walls, floors and ceilings in point clouds, under the assumption of Manhattan-World (MW) buildings. MW was first defined by Coughlan & Yuille (1999); these buildings have three mutually orthogonal directions and the coarse objects' relationships have distinctive rules, for example the floors and ceilings are horizontal, whereas the walls are vertical and are either parallel to the y-z or the x-z planes. The proposed algorithm achieves the detection of the above-mentioned objects with limited human intervention and low computational complexity. Another major contribution of this algorithm is that it can be applied to entire point clouds of buildings, and not only on isolated rooms.

In the following paragraphs, the state of research is presented, followed by the detailed description of the proposed algorithm: its input, the main steps, and the expected output. The experimental section presents the results obtained by applying the proposed method to extract the BIM model of an office building. The last section concludes the paper and discusses directions of future research.

2. Related Work

Object detection in point clouds is a well-studied topic. Therefore, in this section we will only present the papers that are closest to our approach. Valero et al (2012) used Radio Frequency Identification tags prior to laser scanning the facility, so that they could obtain information regarding the objects. Jung et al (2014) proposed a semi-automated process for the creation of as-built BIM for indoor environments using point clouds. Specifically, point clouds are converted into geometric drawings where lines are given to guide the manual modelling, reducing the modelling time. The process consists of three steps: segmentation, refinement and boundary tracing.

Pu and Vosselman (2009) detect major objects which define building facades, such as walls and roofs. To detect these objects they use predefined human knowledge such as the size, position, orientation, topology and point density. In our method, we determine similar characteristics to infer the object class. Sanchez & Zakhor (2012) classify coarse objects by comparing the angles of normal with the x and y axis. This approach however fails to address the case of highly cluttered environments: e.g. it is not able to distinguish between bookshelves and walls. Hong et al (2015) proposed an algorithm for the accurate creation of as-built BIMs. They first model horizontal planes (floors, ceilings) by estimating the z difference between the highest and lowest surface. The vertical planes are projected onto the horizontal and the boundary is extracted. Even though the accuracy of the proposed solution is encouraging, the method does not address the issue of a multiple room floor. Also, the research addresses planar surface modelling and not solid modelling as needed to generate BIMs.

Xiong et al (2013) and Adan & Huber (2010) examined the detection of coarse objects in interior environments. In the first paper, the researchers use machine learning to classify planar patches based on their contextual features, whereas in the second paper, the authors detect walls by voxelizing the space and determining the major plane regions exploiting geometric characteristics. Other objects, such as openings, are distinguished using an SVM classifier. Both cases offer promising results in labelling walls, floors and ceilings in cluttered environments.

Furthermore, object classification techniques for geometry generation in a story with multiple offices has been examined (Thomson & Boehm 2015, Ochmann et al 2016). Ochmann et al (2016) exploits contextual information by first segmenting the data into rooms. They used a top-down approach compared to our bottom-up. Thomson & Boehm (2015) presented an Industry Foundation Class generation process using spatial information. We build and further expand on this spatial reasoning for more robust object classification.

More specifically for MW buildings, grammar based methods where investigated (Vanegas et al 2010, Khoshelham & Díaz-Vilariño 2014, Becker et al 2015). The rules set are rather restrictive and can only be applied to specific scenarios, e.g. in floors with long hallways. Xiao and Furukawa (2012) reconstructed the world's museums, by taking advantage of the fact that most of the museums' geometry is cuboid. Hence, they could fit cubes in the point cloud data. The point cloud was sliced in 2D pieces. The researchers extracted lines in each piece and fitted rectangles, the 2D solid models were finally stacked to create the 3D model. In this case, the researchers managed to create a volumetric 3D model, but the classification of the objects is not performed. Therefore, the user has to manually determine the different objects in the scene.

We aim at developing a novel algorithm that can detect and classify each object separately in a cluttered MW building in order to address these limitations. As BIM necessitates solid modelling and not simple surface modelling, the objects of interest are represented through volumetric models when possible, e.g. a wall consists of a vertical cuboid, and not only a planar surface. Also, the minimum human intervention, the reduced computational complexity and the simplicity of the algorithm add up to the contribution of the paper.

3. Proposed Algorithm

The outline of the algorithm for detecting walls, floors and ceilings is presented in Figure 1. First, the algorithm takes as input a Point Cloud Data (PCD). The PCD is considered to be a set of point clouds which are registered and aligned to the major axis. Since these operations can be performed using the proprietary software accompanying laser scanners, they are not examined in this paper. The point cloud is then segmented into planar surfaces using RANSAC for point cloud shape detection as described in Schnabel et al (2007). RANSAC is an iterative algorithm, which tries to find the parameters of the model that best fits the data, while filtering out the outliers. This step outputs the point cloud segmented into a number of planar surfaces. We focus on obtaining planar surfaces based on the assumption that the coarse objects being examined are clearly planar. The planar segments are extracted in a descending order based on the number of points to facilitate the subsequent processing steps. Also, the position and normals of the segments are computed. These data assist in the determination of the orientation of the segments. The point cloud is then projected onto the y-z plane and the x-z plane, octree division is applied and the octrees with the maximum number of points are acquired. This leads to the detection of the horizontal planar surfaces that correspond to the floors and ceilings. Subsequently, we remove the majority of the present clutter by keeping the vertical planar surfaces that satisfy specific criteria. The rest of the segments are divided into two categories: the one that are parallel to the y-z plane and the x-z plane, we keep the planar surfaces in the perimeter that are within a minimum distance from the bounding box of the point cloud and we merge the planar surfaces that correspond to cuboid walls. The remaining segments are discarded. The final result contains the detected walls, floors and ceilings. In the following paragraphs, each step is explained in detail.

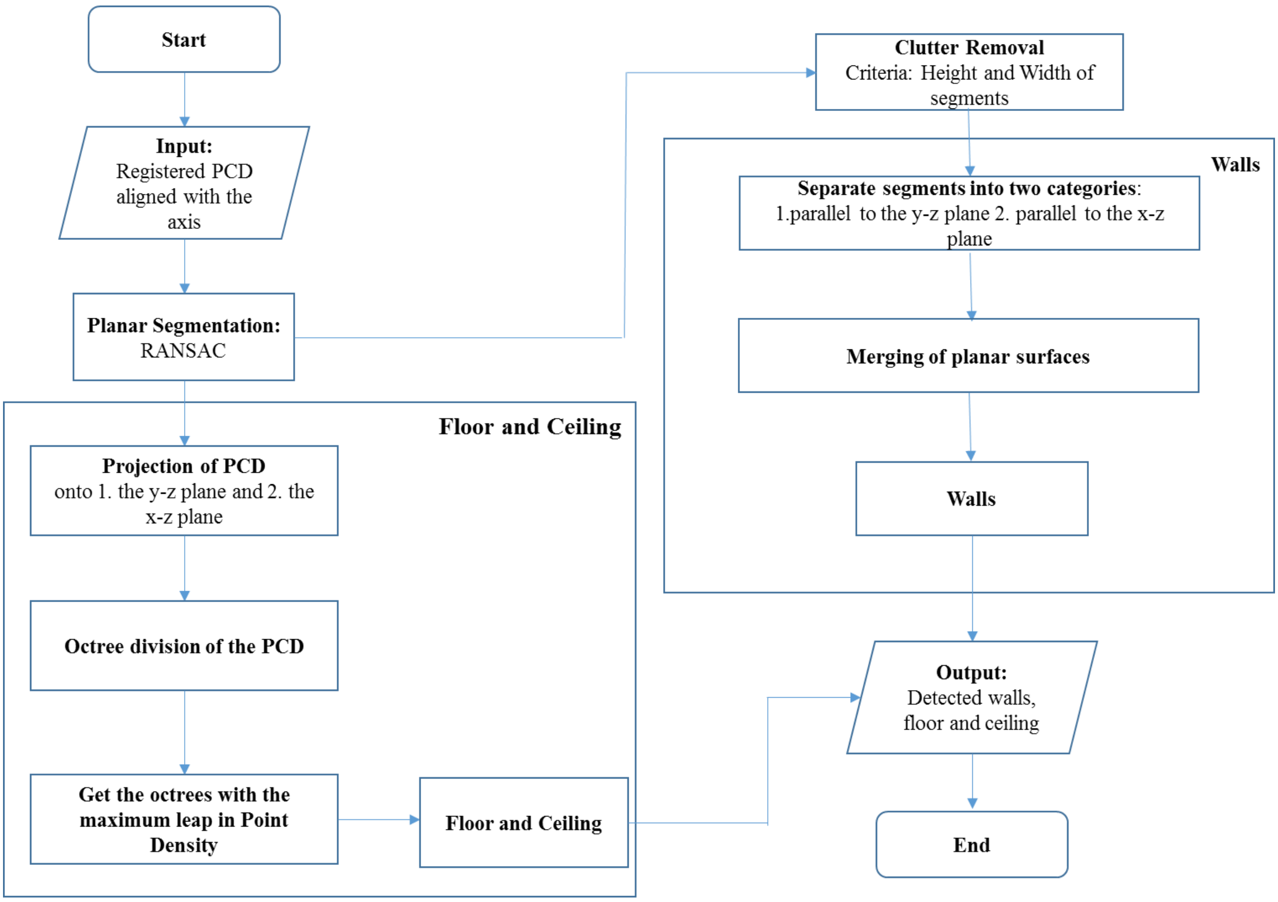

Figure 1. Flow chart of the proposed solution

3.1. Floor and Ceiling

Since the point cloud is aligned with the axis and we consider an MW structure, the floor and ceiling are horizontal and parallel to the x-y. Therefore, the points corresponding to these objects are concentrated on specific values of z that have to be identified. To this end, we project the point cloud into the y-z and the x-z plane back to back, acquiring a straight line of points on the z axis with different point density. In order to identify the z values where most of the points are concentrated, we use octree division which is an efficient algorithm for partitioning the 3D space (Meagher (1982)).

We extract the point density in each octree cell having applied the octree division to the projected PCD. By comparing the percentage difference of the point density of one division with the previous and following two octree divisions, we keep the octrees that satisfy a predefined threshold. The horizontal planar segments that have been extracted by the segmentation step, and which contain the points of the octree divisions identified in this step are classified as floors and ceilings. The rest of the horizontal segments are discarded.

Object	***Criteria***
Floor & Ceiling	$abs(PointDensity[i] - PointDensity[i+1])/PointDensity[i] > 1$
Interior Walls in the minor axis (x-z)	• $(maxPoint.z - minPoint.z > Thresh)$ && $(maxPoint.x - minPoint.x > Thresh)$ • $LowerThres < abs(PositionX[i] - PositionX[j]) < UpperThres$ • $abs(MaxX[i] - MaxX[j]) < UpperThres$
Interior Walls in the major axis (y-z)	• $(maxPoint.z - minPoint.z > Thresh)$ && $(maxPoint.y - minPoint.y > Thresh)$ • $LowerThres < abs(PositionY[i] - PositionY[j]) < UpperThres$ • $abs(MaxX[i] - MaxX[j]) < UpperThres$
Perimeter Walls	Minimum Distance from the Bounding Box

Table 1. The proposed criteria for the detection of objects in the point cloud

3.2.Clutter Removal and Walls

Even though in MW buildings walls are considered to be orthogonal and perpendicular to the x-y plane, they stand a greater challenge compared to floors. Their length as well as their position in 3D space varies based on the configurations of the rooms in the interior. Additionally, a wall in an interior environment is not a simple planar surface but a pair of planar segments, since the same wall is laser scanned from both sides from two different rooms -- a detail that adds up to the difficulty of defining the walls in interior environments.

We extract the planar surfaces which have normals parallel to the x-z and y-z plane. The algorithm discards all these segments whose difference between the maximum x or y coordinate and minimum x or z coordinate is below a threshold for the segments parallel to y-z or x-z planes respectively. In this case, most of the clutter which is present in the interior is rejected.

The algorithm finally detects the boundary walls of the structure and the planar segments that correspond to interior walls after having removed most of the clutter from the point cloud. Please note that clutter usually affects the completeness of the object in the point cloud, however, our algorithm assumes that objects are not fully covered by clutter. For the boundary walls of the structure, the algorithm keeps the first planar surfaces which are in the minimum distance from the bounding box surrounding the point cloud.

To connect the planar segments which form a wall, we consider two directions the x-z and y-z axis and the positions of the segments acquired from RANSAC as mentioned above. The examined segments i and j in the x-z direction are considered as one wall as long as the following statements are true:

$$LowerThres < abs(PositionX[i] - PositionX[j]) < UpperThres \quad (1)$$

$$abs(MaxY[i] - MaxY[j]) < UpperThres \quad (2)$$

The first relationship (1) compares the Position in the x direction of the two surfaces, whereas the second (2) compares the y distance of the segments. (1) guarantees that surfaces lying on the same level on the x axis do not get connected, whereas (2) guarantees that the distance in the y direction does not surpass an upper threshold. Similarly for the y-z. The above thresholds derive from the common knowledge that walls have a specific width. The presented thresholds (Table 1) are not static. Alas, the

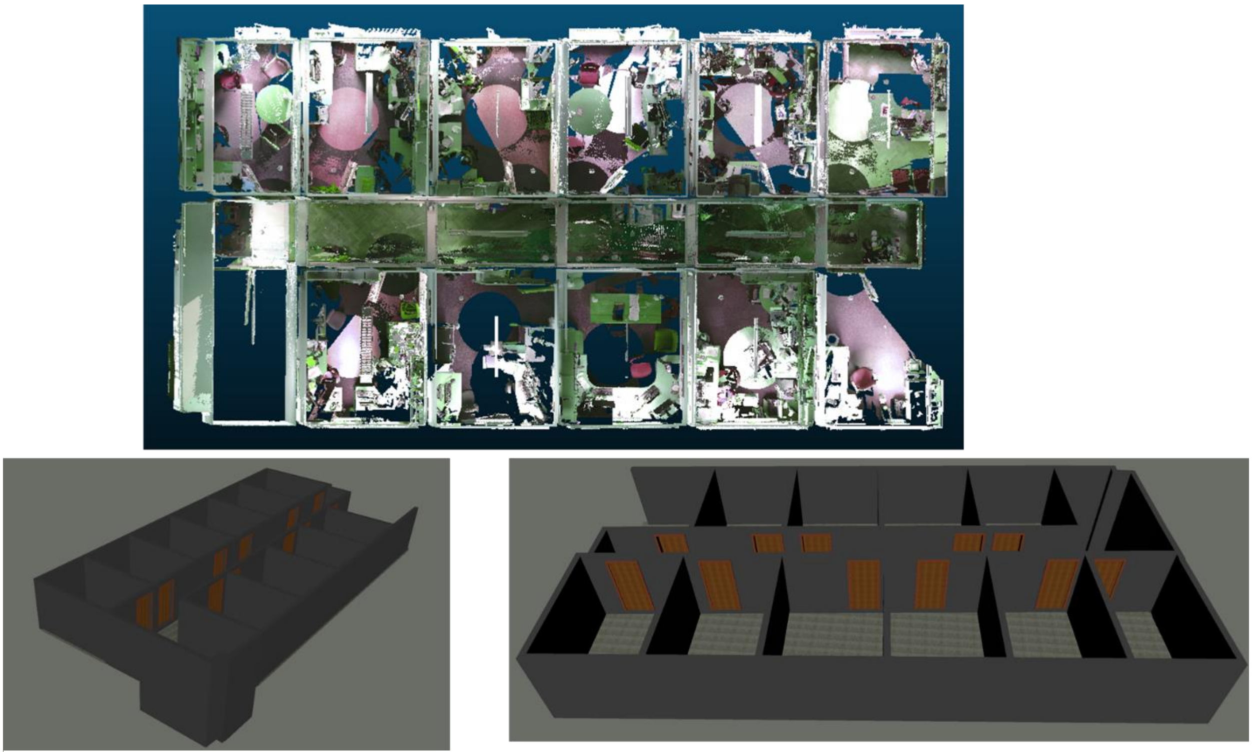

Figure 2. The top image shows the original point cloud. The bottom images show the 3D model manually created using Revit

user has to adjust them based on the site conditions. For example, if the estimated width of the walls are about 15cm, the user can adjust the UpperThres of equation (2) to 25cm taking into consideration the noise in the data.

4. Experiments and Results

The proposed algorithm is applied on a floor of an office building. The examined MW structure is the Baker Building of the Engineering Department of the University of Cambridge. The laser scans have been first registered and aligned to the x-y-z axis. The floor consists of 11 offices, (out of which 10 have been fully laser scanned), a main corridor and a stairwell. The building is in use, therefore the scans are cluttered. The original point cloud) can be seen in **Figure 2** top row. It consists of 94,143,512 colored points. Color has been discarded since our algorithm relies purely on geometry, ignoring appearance cues. Also, the PCD has been downsampled to two million points. This drastic operation (discarding 97% of the original point cloud) was performed to ensure a fast execution during RANSAC segmentation. However, since planar surfaces can be estimated from a small number of points (only three points are needed in the ideal case), the downsampling does not affect the final results. The segmentation returned 392 planes with the largest one containing 294,840 points corresponding to the floor. The parameters describing the planar surfaces, e.g. normals and position are extracted by the algorithm in a txt format.

By visual inspection, we are able to identify the minor and the major axes as being xz and yz respectively, and set the corresponding thresholds. Finally we fed all the clusters to our algorithm. The results are shown in **Figure 3**.

We have manually generated the 3D model of the point cloud using Revit (see Fig. 2 bottom row), and clustered the points that belong to the same primitive (Figure 3c) in order to evaluate the accuracy of the proposed approach. The manual labelling of the segments has shown that we have 13 segments that correspond to the ceiling and one large planar surface corresponding to the floor. 13 segments correspond to the perimeter walls, while the number of cubic interior walls is 12. The final results and accuracy are grouped in **Table 2**. The results show that the precision for floor, ceiling is 100%, for exterior walls is 86.7%, whereas for the interior walls, the precision reaches 92%. The false positive for the interior walls in the algorithm is the light pink segment shown in Figure 3f, which corresponds to the staircase handrails.

Objects	**Manually Detected Segments**	**Automatically Detected Segments (True Positive)**	**Automatically Detected Segments (False Positive)**
Floor	1	1	0
Ceiling	13	13	0
Exterior walls	13	13	2
Interior Walls	12	12	1

Table 2 Results of the conducted experiment.

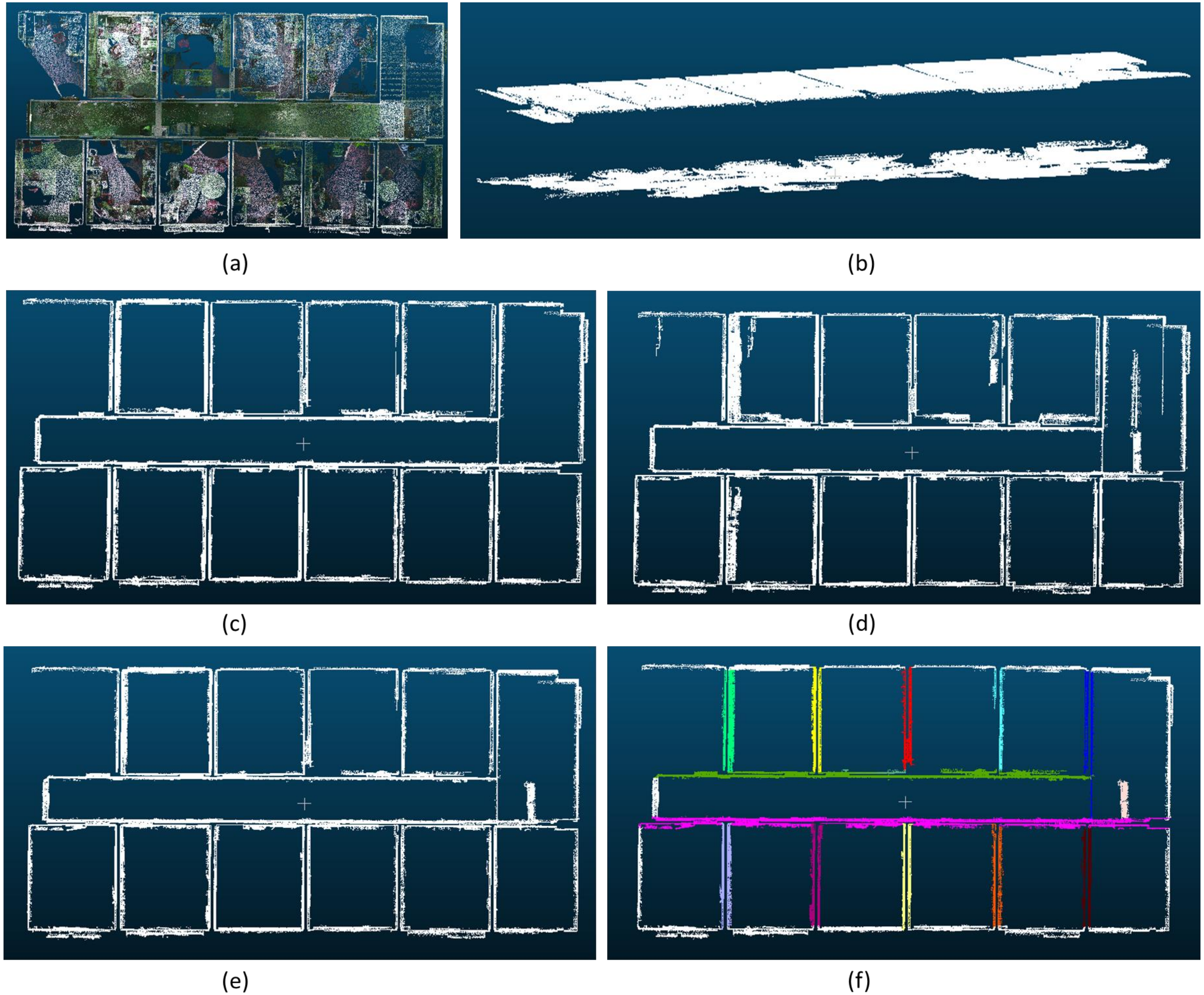

Figure 3. a) The downsampled point cloud, b) the final result for the floor and ceiling, c) the ground truth detection, d) first pass of clutter removal, e) detected walls, f) the different pairs of walls having been detected in color, the perimeter walls in white.

5. Conclusions

Building Information Models for existing facilities are useful for renovation, facility management and retrofitting purposes. BIMs, however, need a high level of detail to achieve the above purposes. Point clouds can only offer information regarding the objects visible with a naked eye. Hence, they can only assist in the first level of detail of BIMs. In our research, we aim in facilitating the creation of 3D models. We proposed an algorithm which successfully detects floors, walls and ceilings in Manhattan-World structures. The algorithm uses simple geometric priors to determine which planar surfaces correspond to the sought structural elements. It is divided into two sections, one referring to the horizontal surfaces and the second to the vertical surfaces. The algorithm has been tested in a laser scanned point cloud. We have proven that the precision is over 86% and issues regarding the clutter have been successfully tackled. Hence, our goal of minimizing the manual effort needed to detect structural elements in a building has been significantly accomplished.

However, this is only the first step in creating 3D models from point clouds. Our next goal in this process of capturing the as-is conditions is the generation of IFC models. We have extracted the dominant structural elements and we can now extract information regarding their length, width, height and position, which will constitute the basis for the IFC model generation. It is important to further examine how clutter affects the accuracy of the created IFC model, since clutter affects the completeness and accuracy of the object.

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