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FEASIBILITY AND ACCURACY OF AS-BUILT MODELLING FROM SLAM-BASED POINT CLOUDS: PRELIMINARY RESULTS

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ABSTRACT:

Nowadays, portable Mobile Mapping Systems (MMSs) and robotic mapping platforms leveraging on Simultaneous Localization and Mapping (SLAM) methods are gaining increasing attention for architectural and construction surveying, representing an efficient solution for geometric data acquisition for scan-to-BIM purposes. However, the applicability of standard modelling workflows and the accuracy of Building Information Models (BIM) that can be obtained from SLAM-based point clouds is still an open question. In this paper, we propose a preliminary evaluation on the feasibility of extracting as-built BIM from (i) a point cloud acquired with a commercial portable MMS, and (ii) a point cloud obtained through an open-source SLAM algorithm, surveying the environment with an autonomous mobile robotic platform. In both cases, the main structural elements of the test site are accurately generated, thus showing promising results. On the other hand, the experiment highlights also the need for SLAM systems capable of providing less noisy point clouds, in order to capture and model architectural details.

1. INTRODUCTION

In recent years, we are witnessing an increasing popularity of portable Mobile Mapping Systems (MMSs) which can drastically reduce acquisition time, making surveying operations more efficient and cost-effective. Relying on Simultaneous Localization and Mapping (SLAM) technology to make up for Global Navigation Satellite System (GNSS) unavailability, portable laser scanners, in fact, allow to easily map the surroundings simply by walking through the area of interest (Di Filippo et al., 2018). The characteristics and working principles of such systems make them ideal for fast indoor surveying, supporting, e.g., facility management (Cantoni and Vassena, 2019) and functional analysis of building spaces (Comai et al., 2020). Furthermore, thanks to their compactness and ease of use, portable MMSs find application also in outdoor scenarios, from forest inventory (Proudman et al., 2022) to cultural heritage site documentation, frequently coupled with other geomatics techniques in a multi-sensor approach (Chiabrando et al., 2019, Maset et al., 2022b). In addition to backpack, trolley, and handheld MMSs, which still require a surveyor to operate, sensorized robotic platforms leveraging on SLAM algorithms will become widespread in the near future, opening up the possibility for automated mapping (Maset et al., 2022a). Mobile robots equipped with laser scanners, RGB cameras and multispectral sensors are increasingly used in the field of precision agriculture (Tiozzo Fasiolo et al., 2022b), but the employment of autonomous systems is also spreading for the digitization of buildings, as reviewed in (Adán et al., 2019).

On the other hand, the use of the Building Information Modelling (BIM) paradigm and the demand for as-built BIM models are growing in Architecture, Engineering and Construction (AEC) industry (Banfi, 2017, Banfi, 2019), being critical for a variety of applications, including as-built vs as-designed analyses, change detection and construction progress monitoring (Previtali et al., 2020, Sgrenzaroli et al., 2022). For existing buildings, BIM modelling turns into a problem of reverse engineering based on 3D point clouds, referred to as the *scan-to-BIM* process (Wang et al., 2019). Traditionally, Terrestrial Laser Scanning (TLS) and photogrammetry are the most common surveying techniques employed to gather accurate geometric data for the subsequent scan-to-BIM procedure. However, acquisition and post-processing steps required by such solutions are time consuming, and can represent a bottleneck when there is a need for easy-to-use devices and rapid mapping operations.

In this context, it becomes crucial to understand the potential and limitations of efficient scanning technologies such as portable mapping devices, with respect to the scan-to-BIM process. For this reason, this paper proposes a preliminary analysis on the feasibility of extracting an as-built BIM model from (i) a point cloud acquired with a commercial portable MMS, and (ii) a point cloud obtained through an open-source SLAM algorithm, surveying the environment with an autonomous mobile robotic platform.

2. RESEARCH QUESTION AND RELATED WORKS

Since the appearance of portable laser scanners on the market, numerous studies have assessed their performance, comparing the point clouds obtained from SLAM-based instruments with reference ones, provided by well-established geomatics techniques such as TLS and photogrammetry. For instance, in (Nocerino et al., 2017) handheld and backpack systems are tested for the indoor survey of a building and for the outdoor mapping of a city square. The work by (Tucci et al., 2018) quantitatively analyzes three commercial systems for the survey of an ancient building. Furthermore, in (Maset et al., 2021) the accuracy and noise level provided by a handheld device are evaluated in different outdoor scenarios. A comprehensive review and classification of commercial mobile indoor mapping systems can be found in (Otero et al., 2020), in which the authors underline the characteristics of interest for architectural and construction applications. Overall, these works agree in

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pointing out a high completeness of the point clouds obtained with portable MMSs, with accuracy level ranging from a few centimeters to 10 cm. However, they also highlight the lower density and higher noise that characterize such devices, which in turns reduces their ability to reconstruct architectural details.

On the contrary, the quality of 3D point clouds acquired with sensorized robotic mapping platforms is not deeply analyzed in the literature (Adán et al., 2019). Within the robotics community, the focus is mainly on localization and navigation tasks, and few researches are devoted to the quantitative assessment of the point cloud accuracy obtained through mobile mapping robots coupled with the SLAM approach. Among them, we can cite the paper by (Tiozzo Fasiolo et al., 2022a), that compares the results provided by an autonomous platform equipped with a laser scanner with respect to a TLS ground-truth model.

Regarding the scan-to-BIM application, an increasing number of papers propose the evaluation of mobile and portable mapping systems for as-built BIM modelling purposes (Rashdi et al., 2022). However, these works usually limit the analyses on the characteristics of the point clouds, especially in terms of accuracy, noise, density and completeness (Plaß et al., 2021, De Geyter et al., 2022, Dlesk et al., 2022). The next question that arises is whether a modelling workflow, originally designed for geometric data acquired through TLS or photogrammetry, can be successfully used with point clouds derived from SLAM technology, and what is the quality of the BIM models that can be extracted. To this end, in (Sammartano et al., 2021) the authors evaluate the applicability of triangulation and NURBS generation to a MMS point cloud, to obtain the parametric model of several architectural elements characterized by complex geometry. Focusing the attention on time-efficient methods, in this work we evaluate a further step towards the automation of data acquisition and model extraction, assessing feasibility and accuracy of as-built modelling from SLAM-based solutions. In the view of maximizing automation and limiting the processing time, the models are created using semi-automatic scan-to-BIM functions, that aid the modelling step.

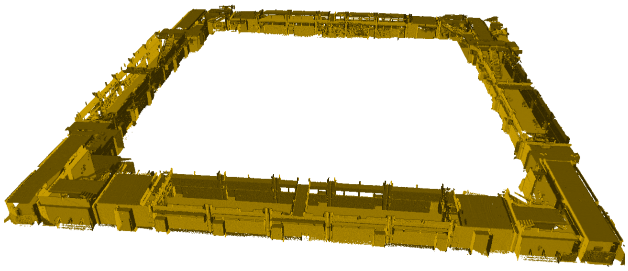
3. MATERIAL AND METHODS

As case study, we chose the ground floor of the west-wing corridor of the Rizzi building, located in the scientific campus of the University of Udine (Italy). The squared-plant area of dimensions 80 m $\times$ 80 m was firstly mapped using the handheld MMS HERON Lite by Gexcel srl (Fig. 1(a)), whose sensor head consists of a Velodyne Puck LITE laser scanner and an Xsens MTi inertial measurement unit. The scanning device is able to measure up to 300,000 points/s at a maximum distance of 100 m, with a precision of $\pm$3 cm, and the sixteen channels that emit infrared laser pulses allow to cover a 360° horizontal field of view and a 30° vertical field of view. The sensor head is installed on a telescopic pole and connected to a battery and a control unit for real-time data visualization.

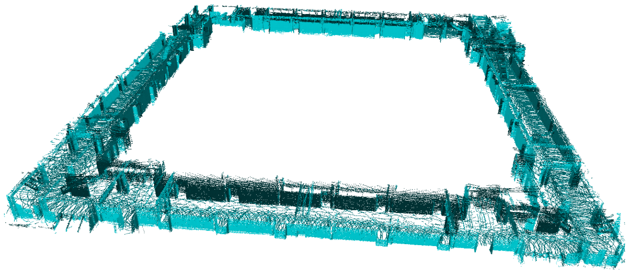
The survey of the test site lasted approximately 5 minutes, with the operator following a closed-loop trajectory with starting and ending point on the south part of the corridor. The acquired data was then post-processed using the proprietary software HERON Desktop, characterized by a two-step SLAM approach. The first one implements an on-line SLAM method to retrieve an estimate of the sensor trajectory. The second stage divides the trajectory into local maps and aligns them all simultaneously, according to a full SLAM strategy (Grisetti et al., 2010). This last procedure allows to take into account loop closures along the survey path (i.e., revisited areas), minimizing drift and residual misalignments errors. A view of the obtained point cloud is reported in Fig. 2(a).

(a) Handheld MMS. (b) Mobile robotic platform.

Figure 1. (a) Commercial handheld MMS (HERON Lite by Gexcel srl) and (b) autonomous mobile robotic platform (Scout Mini by Agile-X Robotics) equipped with a Velodyne VLP-16 laser scanner.



(a) Point cloud from handheld mapping.



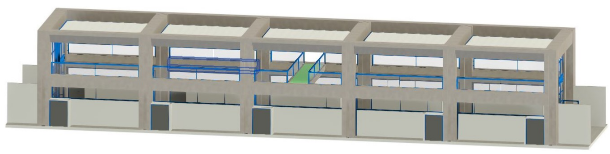
(b) Point cloud from robotic mapping.

Figure 2. Point clouds obtained from (a) the handheld MMS, and (b) the robotic survey.

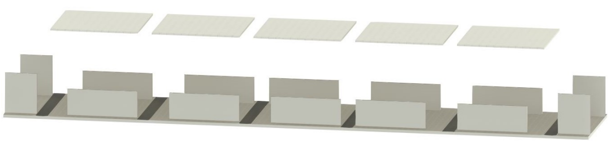
Following a similar trajectory, a second survey was autonomously performed by the Agile-X Scout Mini mobile robot (Fig. 1(b)), a four-wheeled compact platform equipped with a Velodyne VLP-16 laser scanner and a NVIDIA Xavier computer for data acquisition management and navigation capabilities. Please note that the laser scanner specifications are equivalent to those of the commercial handheld device described above. In this case, the final point cloud, shown in Fig. 2(b), was retrieved applying the open-source SLAM algorithm known as *hdl_graph* (Koide et al., 2019), that was proved to provide a good trade off between accuracy, point density and computational load (Tiozzo Fasiolo et al., 2022a). More in detail, this SLAM approach uses the Normal Distributions Transform (NDT) (Biber and Straßer, 2003) instead of the traditional Iterative Closest Point (ICP) approach as scan matching algorithm between consecutive scans. Furthermore, it is able to exploit loop closures along the trajectory and introduces the ground plane constraint, i.e., the assumption that the survey environment has a single flat floor, which makes *hdl_graph* ideal for indoor scenarios.

The subsequent extraction of the parametric model and the evaluation of the results were performed focusing on the south part of the surveyed corridor, characterized by a rectangular plant of dimensions 42 m $\times$ 7 m and a height of approximately 7 m, with a regular and repetitive geometry. The Leica BLK360 G1 terrestrial laser scanner was employed to obtain the ground-truth point cloud of the area of interest, shown in Fig. 3(a). This small-size and lightweight scanning device (height of 165 mm, diameter of 100 mm and weight of 1 kg) is integrated with three 15 Mpixel cameras for spherical image acquisition. The instrument emits infrared signals of wavelengths 830 nm and allows to reach a 360° horizontal field of view and a 300° vertical field of view. The employed TLS has a minimum measuring range of 0.60 m and a maximum range of 60 m, managing to achieve millimeter accuracy (according to the manufacturer's specifications, 4 mm at 10 m, and 7 mm at 20 m). To obtain a complete point cloud of the corridor, five scans were performed at a distance of approximately 9 m from each other, each lasting 2 minutes and 50 seconds. The individual point clouds were then aligned through the ICP approach implemented in the Leica Cyclone Register 360 BLK Edition software, without the use of reflective targets. A global alignment error of 2 mm was finally estimated by the software.

(a) TLS point cloud.



(b) Complete model of the corridor.



(c) Structural elements considered in the evaluation.

Figure 3. (a) Ground-truth point cloud, acquired with a TLS. (b) Complete as-built BIM model, manually generated from the TLS data. (c) Walls, floor and ceiling used in the evaluation stage.

After the removal of outlier points, the TLS data were used within Autodesk Revit software for a manual scan-to-BIM process, that led to the generation of the reference model. This includes all structural and architectural elements of the corridor, as illustrated in Fig. 3(b). More in detail, the TLS point cloud was first imported in the software and longitudinal and transversal sections and planes were defined to facilitate subsequent operations. The model was then created by inserting elements that belong to different families: some of them (such as walls, floor and ceiling) are basic components, already available in the software libraries, while other elements like beams, columns, windows, doors and complex profiles were specifically modeled and parameterized. Following this manual modelling approach provided a high accurate output, with millimeter deviations between the model and the respective point cloud. However, the result came at the cost of very time-consuming manual operations.

As for the SLAM-based point clouds, they were firstly aligned to the TLS one through the ICP algorithm implemented in CloudCompare software. Then, the modelling procedure was carried out in a semi-automatic fashion: floor, ceiling and wall elements were obtained using the *As-Built for Autodesk Revit* plug-in by FARO, that allows the fast extraction of best-fit planes. In fact, through the random selection of a number of points on the point cloud, the plug-in is able to automatically fit a plane for the construction of horizontal surfaces. A similar approach was also followed for modelling wall elements: after identifying the wall type and selecting two points, the software fits the vertical wall to the point cloud. Since only one side of the walls was scanned, the wall thickness was manually defined. This approach undoubtedly speeded up the scan-to-BIM operations, leading to the models evaluated in the following section.

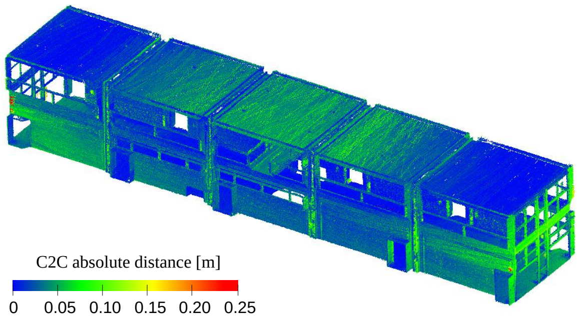
4. RESULTS AND DISCUSSION

As first preliminary assessment of the scan-to-BIM process, a validation of the SLAM-based models was performed by computing the deviation between the parametric models and the respective point clouds, from which they were generated. This analysis was carried out directly within the semi-automatic modelling plug-in, using the *surface analysis* function. The mean values, reported in Tab. 1, ranges from few millimeters to 1.2 cm, confirming the effectiveness of the best-fitting plane procedure. On the other hand, the Root Mean Square (RMS) values can be interpreted as a measure of the noise level that characterizes the SLAM-based point clouds. The results for the handheld MMS are in accordance with the manufacturer's specifications, and consistent also with the outcomes of the work by (Maset et al., 2021). Furthermore, it can be noticed that the point cloud acquired with the robotic platform is noisier.

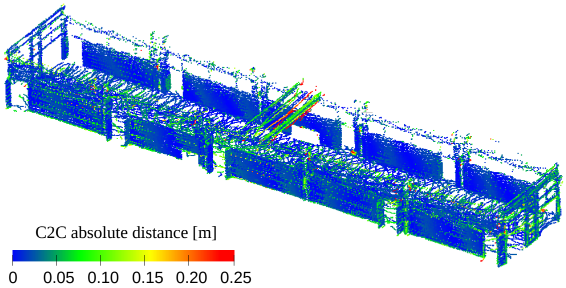
Element	Handheld		Robotic	
	mean [m]	RMS [m]	mean [m]	RMS [m]
Walls	-0.004	0.016	-0.003	0.023
Floor	-0.011	0.020	-0.012	0.027
Ceiling	-0.006	0.020	n.a.	n.a.

Table 1. Deviation between the parametric models and the respective point clouds, from which they were generated. Due to the low point of view and the limited vertical field of view of the laser scanner mounted on the robotic platform, the ceiling was not surveyed and is missing in the corresponding model.

The comparison between SLAM-based results and TLS ones was then carried out both at the point cloud and at the model level. As traditionally done in the literature, the performance of the handheld and robotic mapping systems was first evaluated in terms of Cloud-to-Cloud (C2C) distances (computed in CloudCompare software), shown in Fig. 4. An average value of 0.021 m ($\pm$ 0.017 m) was obtained for the handheld point cloud, and of 0.026 m ($\pm$ 0.031 m) for the robotic one, which testifies the good accuracy provided by the SLAM approaches. Although the quite long trajectory (approximately 320 m), both commercial and open-source SLAM algorithms managed to minimize drift accumulation. Analyzing more deeply Fig. 4(a), higher

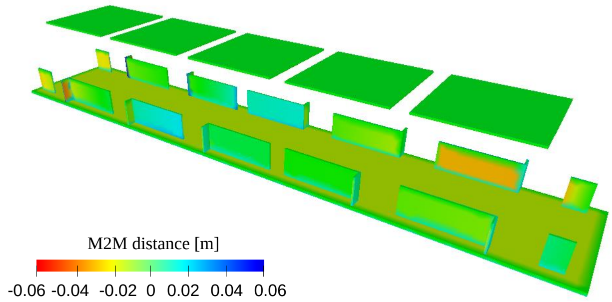


(a) Handheld mapping.

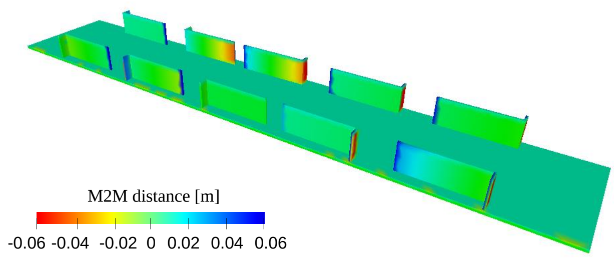


(b) Robotic mapping.

Figure 4. C2C absolute distances computed between the TLS point cloud and (a) the one acquired with the handheld device, (b) the point cloud obtained with the mobile robotic platform.



(a) Handheld mapping.



(b) Robotic mapping.

Figure 5. M2M distances computed between the TLS-derived model and (a) the model created from the handheld MMS point cloud, (b) the model obtained from the point cloud acquired with the robotic mapping system.

distance values can be noticed in the central part of the corridor. These are due to a slight deformation of the handheld MMS point cloud, that shows a *arch-like* shape on the floor and ceiling, already highlighted also in (Maset et al., 2021). A possible explanation of such effect lies in the repetitive geometry of the environment, which makes the scan matching phase more challenging and prone to error, resulting in local deformations.

Element	Handheld vs TLS		Robotic vs TLS	
	RMS [m]	max [m]	RMS [m]	max [m]
Walls	0.023	0.069	0.033	0.175
Floor	0.023	0.023	0.022	0.022
Ceiling	0.004	0.008	n.a.	n.a.

Table 2. Results of the model-to-model comparison.

To assess the quality of the models created, main focus of this work, Model-to-Model (M2M) distances with respect to the TLS-derived BIM were estimated, using the *Distance from reference mesh* function implemented in MeshLab software. For the comparison, only floor, ceiling and wall objects of the TLS model were taken into account (Fig. 3(c)). The results, presented in Fig. 5 and summarized in Tab. 2, are encouraging, with RMS values ranging from few millimeters for the ceiling extracted from the handheld point cloud, to 0.033 m for the walls created from the robotic data. Overall, handheld and robotic systems provide comparable model accuracy. Furthermore, thanks to the automatic best-fitting of planar elements, the difficulty of modelling objects on a noisy point cloud is partially reduced.

On the other hand, the high maximum error values of the wall elements reported in Tab. 2 (0.069 m for the handheld case and 0.175 m for the robotic data) derive from the low level of detail that characterizes the SLAM-based point clouds. In fact, the combination of low surface density and high noise level made

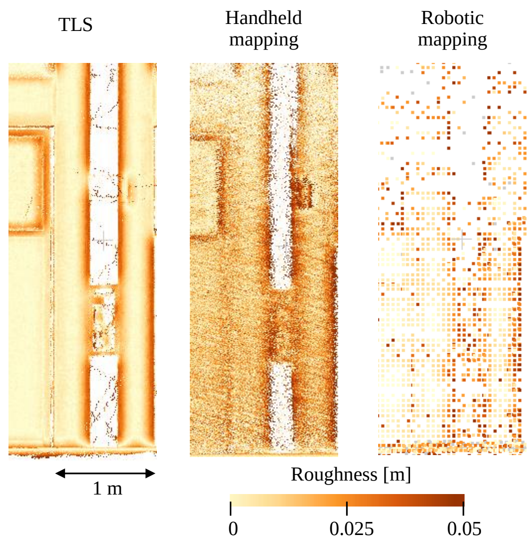


Figure 6. A portion of the point clouds, which shows the different level of detail provided by the scanning technologies. Points are colored according to the local roughness.

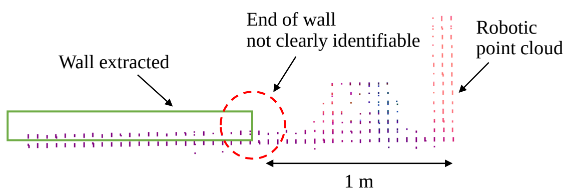
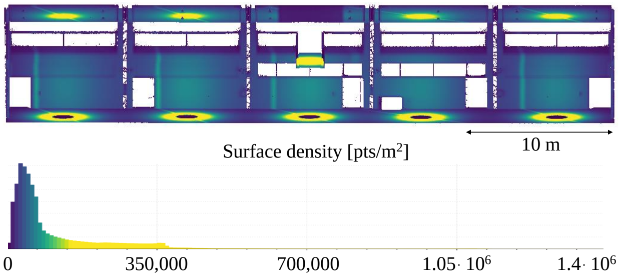


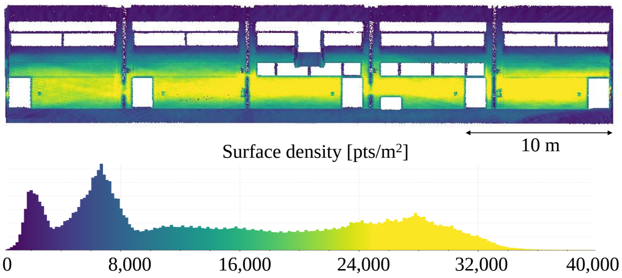
Figure 7. Due to the low density and level of detail of the point cloud acquired with the robotic system, it is difficult to identify the end of the wall.

it difficult to identify the wall limits. This is clearly evident in Fig. 6, where the boundary between the wall and the adjacent column can be easily identified on the TLS point cloud, is less recognizable in the handheld one, and is not visible at all in the robotic map. As a consequence, in some cases the end of the wall was erroneously determined, as schematized in Fig. 7.

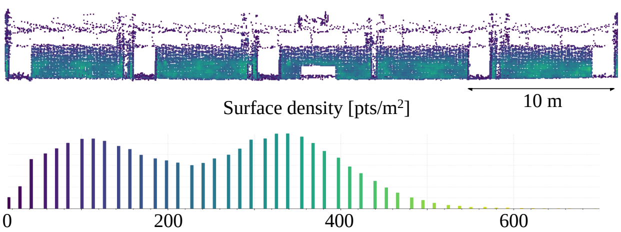
A more in-depth analysis of the surface density distribution that characterizes the evaluated point clouds is shown in Fig. 8 and Tab. 3. In support of the results previously discussed, the mean density of the robotic point cloud turned to be three orders of magnitude lower than the TLS one. The handheld point cloud, on the contrary, presents high density values on the walls (25,000 points/m^2), which are considerably reduced on the floor and ceiling, due to the limited vertical field of view of the portable laser scanner. Moreover, roughness statistics are shown in Tab. 3, computed as the distance between a point and the best fitting plane estimated on its neighbors (using a radius of 15 cm). The obtained values represent a further confirmation of the higher noise level of the SLAM-based systems.



(a) TLS.



(b) Handheld mapping.



(c) Robotic mapping.

Figure 8. Surface density characterizing the evaluated point clouds. Please note that different display ranges have been used for clarity reasons.

Finally, the analyzed case study also served to highlight the current limitations of automatic modelling tools. In fact, it was not possible to automatically extract the H-shaped columns and beams of the building, with the modelling function that failed to correctly placed such elements, as shown in Fig. 9. Fully automatic modelling methods still appear applicable only to simple, regular geometries, and future developments are required for a

Cloud	Surface density		Roughness	
	mean [pts/m^2]	SD [pts/m^2]	mean [m]	SD [m]
TLS	124,357	189,978	0.004	0.007
Handheld	15,015	9,634	0.014	0.012
Robotic	241	127	0.019	0.017

Table 3. Surface density and roughness statistics.

complete autonomous scan-to-BIM pipeline.

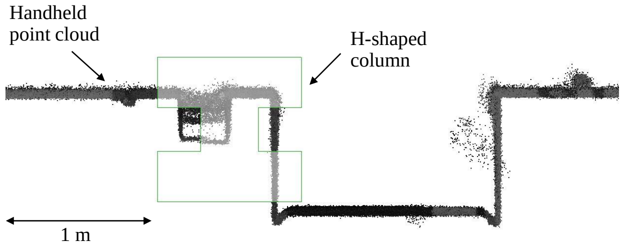


Figure 9. Example of how the semi-automatic modelling tool failed to correctly place the H-shaped column.

5. CONCLUSION

This work presented a preliminary analysis on the feasibility of extracting as-built models from SLAM-based point clouds, acquired by a surveyor through a portable mapping device or obtained by a sensorized autonomous robotic platform. Thanks to the good accuracy of the input data and the use of a semi-automatic modelling process, based on the best-fit of geometric elements that reduces the influence of noise, the results appear promising, with the main structural elements of the test site that were accurately generated. Furthermore, the workflow adopted, from data acquisition to model generation, allowed to significantly speed up the scan-to-BIM process. On the other hand, the experiment highlighted the need for SLAM algorithms capable of providing less noisy point clouds, in order to capture and model architectural details.

The study was carried out in a building characterized by regular (and, thus, controllable) geometry, but a generalization to more complex geometries will be investigated in the future, evaluating as test cases different indoor scenarios. Finally, a key aspect we would like to underline is the importance of analyzing SLAM technologies going beyond the pure evaluation of point clouds, but also focusing on the accuracy and completeness of BIM models that can be extracted from them. This will allow to fully understand the applicability of portable and robotic mapping systems to the scan-to-BIM field.

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