From enriched point cloud to structural and MEP models: An automated approach to create semantic-geometric models for industrial facilities

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ABSTRACT

While helpful for engineering applications, digital models representing the as-is status of the built environment are rarely available and costly to create using conventional methods. Commonly, editable and preferably parametric model geometries are preferred over less easy-to-process, triangulated meshes where possible; additional semantic information beyond the geometry is required in almost any case. We propose an end-to-end method starting from conventional laser-scanned point clouds including RGB color information: The captured data is processed using semantic and instance segmentation and model fitting first to identify semantic clusters and object instances, and then selected structural and MEP elements are reconstructed using geometric primitives and procedural geometric operations such as sweeps to generate meaningful, ready-to-use models. We describe all steps individually, along with a prototypical implementation in which we use state-of-the-art segmentation and reconstruction methods on a real-world dataset collected by the authors. Intermediate and final results are showcased and critically discussed.

INTRODUCTION

All stakeholders and involved parties along the lifecycle of a building can significantly benefit from accurate, up-to-date digital information on the facilities. While the method of BIM (Building Information Modeling) initially focused on the planning and construction phase, its scope is increasingly extended to cover the operation phase (Borrmann et al., 2018). For existing buildings, where usable models are rarely available, the approach of Scan-to-BIM focuses on methods that allow for the generation of as-built or as-is models for further use. As this is conventionally an expert-based, manual, and therefore time- and cost-intensive (Fumarola & Poelman, 2011), many attempts exist to automate this process. Generally, the required steps can be split into data acquisition, processing, and model provision. The requirements for the resulting model vary greatly and depend entirely on the intended use case. For the industrial domain, geometry itself plays an important role, as in industrial buildings, MEP components and supply lines, in general, are often laid openly. In contrast, all building equipment is subject to frequent or cyclic changes (Hullo et al., 2015).

Most current works focus on specific methods to solve single steps or include many manual processing steps to complete an end-to-end workflow; rather than focusing on and optimizing a single step, the modular approach presented in this paper aims to provide an end-to-end workflow by covering all stages from semantically segmented point cloud data to a ready-to-use, semantics-rich procedural 3D model of a typical industrial scene.

BACKGROUND AND RELATED WORKS

As indicated, the domain of Scan-to-BIM has seen an ever-increasing amount of attention and success in recent years. The term was arguably coined around 2010; Tang et al. (2010) reported a comprehensive overview of methods for the automatic reconstruction of building models; Hajian & Becerik-Gerber (2010) provide the first available source that discusses "Scan-to-BIM", concerning computation and productivity aspects. Since then, there have been abundant developments in the above-introduced distinct stages of Scan-to-BIM. For complete end-to-end observations, however, there is still a lack of solutions. Amongst others, Perez-Perez et al. (2021) present semantic segmentation specifically for Scan-to-BIM applications. Andriasyan et al. (2020) present an end-to-end approach to cover historical building model reconstruction- the work of B. Wang et al. (2021) introduces an end-to-end method for generating MEP scenes from scanned data. Until now, these end-to-end methods are limited to specific scopes, such as reconstructing a purely tubular structure (Liu et al., 2022). This paper aims to address the research gap in the current lack of versatile and robust end-to-end methods.

Our previous work focused on combining multimodal data through automated co-registration to automatically reconstruct a simple pipe system model (Pan et al., 2022). In the industrial domain, manual remodeling is particularly challenging, which is why Agapaki et al. (2018) investigated the most frequent and difficult parts to remodel in the industrial context; since they are mainly elongated components, they are classified based on their cross-sectional shape.

For a comprehensive review of the individual steps of the process beyond those mentioned above, we refer to Xie et al. (2019) and Zhang et al. (2019) for semantic segmentation, Oh et al. (2021) and Schnabel et al. (2007) for model fitting and Quintana et al. (2017) and Q. Wang et al. (2019) for model reconstruction approaches.

PROPOSED METHOD

In this paper, we propose a methodology for creating semantics-rich 3D models in the form of procedural geometry from indoor LiDAR point clouds. Building towards a comprehensive, modular toolbox for applicable Scan-to-BIM, our recent work provides an approach to automatically create and enrich 3D models for the simple extract of a pipe system by co-registration of laser-scanned point clouds and photos (Pan et al., 2022). In the reality of industrial facilities, elongated parts such as pipes and steel beams usually occur in combined structures, which we call coherent systems. In the method presented in this paper, the previously proposed methodology is extended to cover more complicated systems of objects and different cross-section types. After introducing the method on a high level, the individual included steps are introduced in more detail in the following.

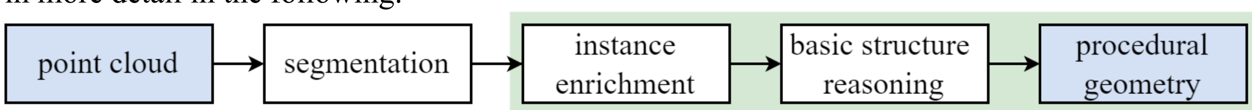

Figure 1: Overview of the proposed method. Green box indicates focus of this paper.

Overview. We aim to automatically reconstruct a usable 3D model based on procedural geometry only (Borrmann et al., 2018) starting from a laser-scan-based point cloud. For this, the point cloud is first enriched with semantic and instance information. This paper focuses on this phase and the subsequent ones, as highlighted within the full context in Figure 1. Based on the identified semantic instance clusters, information is derived to provide the necessary foundation to reason about the basic structure of the semantic systems. This information is then used to combine the instance objects into coherent systems structures of load-bearing and MEP systems. Finally, the geometric models of the systems are recreated using basic methods of procedural geometry, preserving their semantics through knowledge of the individual parts' origins.

Instance enrichment. The method presented in this paper starts from a set of semantic clusters. Instances are separated by means of subsequent region growing to separate pipe systems and cylinder detection using RANdom SAmple Consensus (RANSAC, Schnabel et al., 2007) to identify straight pipe sections and manual instance segmentation (beams). For each instance cluster, we apply several methods to identify the specific parameters necessary for model reconstruction. The applied techniques depend on the object class.

<u>Beams:</u> As the variance of points along the direction of a linear element, such as a beam, is significantly higher than in other directions, principal component analysis (PCA) can be used to identify the point cluster's primary direction and align the beam point cluster with the x-axis. The rotated points are then projected onto the *yz* plane. To extract the value of parameters from the point cloud, a parametric dummy model for an I-beam cross-section is created and instantiated with random values. The shape is parametric and fully customizable using four parameters (cf. Figure 4). To best fit the dummy model to the projected points representing the real beam cross-section, the distance between the points and the edges and vertices of the model must be minimized. Assuming e_i as the shortest distance of the point i to the model, the following fitness function can be defined using the root mean squared error (RMSE):

$$minimize: F(p_1, p_2, \ldots, p_m) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \qquad subjected\ to: l_j \leq p_j \leq u_j \tag{1}$$

where $\{p_1, p_2, \ldots, p_m\}$ are the set of parameter values to define the dummy model, l_j and u_j are the lower and upper bound of each parameter, and n is the total number of points. As the parameters set $\{p_1, p_2, \ldots, p_m\}$ cannot be directly seen in Eq. 1, the derivatives of this function cannot simply be calculated. Therefore, gradient-based algorithms cannot directly minimize the fitness function. Contrary to gradient-based algorithms, metaheuristic algorithms are derivative-free and do not require the closed-form formulation of the objective function. In this paper, we use particle swarm optimization (PSO), as it is easily applicable and can preserve the spatial relationships between the solutions (particles) in the space of the problem. PSO is inspired by the migration pattern of birds (Kennedy & Eberhart, 1995) and requires the following input parameters: the number of particles, the cognitive (c_1), and social coefficient (c_2) as well as the inertia weight (ω).

<u>Pipes</u>: The pipes' cross section is known a priori to be circular, such that its shape can be described by the radius alone. Therefore, we can apply model fitting in the individual straight sections represented in our instance clusters using RANSAC to fit cylinder models with no additional required steps (such as projection) directly in the instance clusters. We have previously described this step in more detail, for which we would like to refer the reader to Pan et al. (2022).

For either class, the start and endpoints of the objects can be identified by projecting all points within a point cluster to the identified center line. These start and endpoints are handed over to the next step to aggregate the individual object instances into coherent systems within a semantic class. The identified cross-section parameters are preserved and finally used in the model reconstruction process.

Basic Structure Retrieval. Individual instance objects have to be connected to form coherent systems to identify the structure of combined elements and enable the reconstruction of a coherent geometry. While the individual instances are known to be connected, they are derived from instance clusters of the point cloud, such that no intersections are included in the derived line representations. We merge them based on their relative pose and proximity to enforce connectivity. We use a hierarchical approach to achieve this:

1. Identify all potential element joints in the system.
2. Classify the joints by type: Join on passing or join free ends, depending on the number of line segments that need to be extended to achieve connectivity.
3. Evaluate each classified potential joint regarding the distance of the closest relevant ends.
4. Prioritize starting from the passing element with the maximum number of qualified joining lines.
5. Iterate join operations for both types of joints until no more potential joints are qualified.

Figure 2: Schematic explanation of the merging of unconnected parts in 2D: Join on passing elements (left) and join of free ends (right)

With this algorithm, we ensure connectivity within systems and generate suitable input for model reconstruction to generate closed-surface geometries.

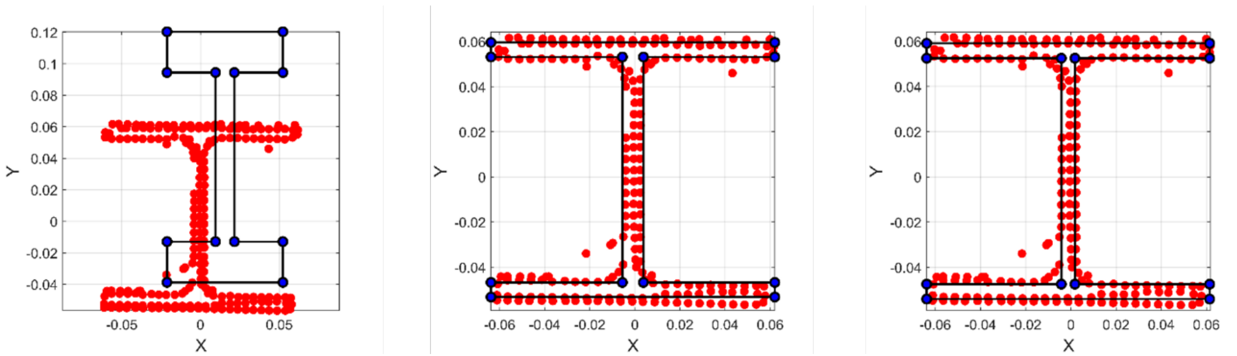

Figure 3: Fitting the cross-section to the point projection using metaheuristic optimization of a parametric shape. Random initialization (left), after 10 iterations (middle), and final result after 100 iterations (right).

Model Reconstruction. Based on the retrieved, combined basic structure, we reconstruct the whole 3D geometries for further usage through procedural geometries (sweeps). All relevant information for this step is retrieved from the previous steps.

EXPERIMENT AND RESULTS

To validate our method and showcase exemplary results, the introduced toolchain is applied to a LiDAR point cloud dataset captured by the authors. The dataset consists of 1’430’000 points captured by a FARO Focus 3D terrestrial laser scanner. Semantic segmentation is performed using the KPFCNN network architecture (Thomas et al., 2019) using synthetic, simulation-based data as ground truth for training (Noichl et al., 2021). Thus, the point cloud is enriched with the class labels of walls, roofs, beams, and pipes. The raw input point cloud is depicted in Figure 2a, and the semantic segmentation results are shown in Figure 2b. Within the pipes class, two pipe systems can be separated using a region-growing approach as presented by Pan et al. (2022), within which RANSAC is applied to identify straight pipe elements and their respective radii (example cf. Table 1). Within the semantic clusters, instances are separated manually for further processing (cf. Figure 5).

Table 1: Model fitting results for an exemplary beam and pipe object.

part	parameter	true [mm]	fit [mm]	deviation [%]
beam	flange width (b_f)	121.8	125.3	2.9
	flange thickness (t_f)	6.9	6.6	-4.5
	beam height (d)	114.6	113.2	-1.2
	web thickness (t_w)	5.6	6.0	7.3
pipe	diameter	353.1	354.2	0.3

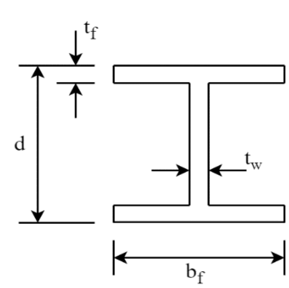

Figure 4: I-beam with dimensions per ASTM A6

PSO is applied with parameters c_1 and c_2 set to 1.49445, and the inertia weight is linearly decreased from 0.9 to 0.4, as recommended in Eberhart & Shi (2001) to maintain the algorithm's stability. Figure 3 shows three stages of the model-fitting process with 35 particles over 100 iterations. After the model-fitting process, the initial random parameter values converge with the real cross-section values measured in the point cloud (cf. Table 1).
The subsequent processing provides the underlying structure of both systems with their center line reconstruction, as depicted in Figure 5e. Finally, these parameters and coordinates are transferred to the open-source CAD tool FreeCAD (Riegel et al., 2022) to create the procedural geometry using sketches and sweeps.
The achieved accuracy of the model fitting for cross-sections used in the sweep operations is further investigated using two arbitrary parts, one pipe and one beam object. Selected results are shown in Table 1. The measured reference values ('true') are manually obtained in the point cloud, and the 'fit' values are obtained by cross-section optimization for the beam using PSO and directly from the result of RANSAC cylinder fitting for the pipe object. The used direction detection by PCA produces results of uneven quality, which significantly affects the projection and model generation steps- we present here only very good results to demonstrate the functionality of our method.

CONCLUSION AND FUTURE WORK

Scan-to-BIM is a versatile, highly active research domain in which concrete implementations depend on the intended use case, requirements, and input data. The presented method starts from a semantically enriched point cloud and produces high-quality procedural models. Apart from one manual step in instance segmentation, it is entirely automated and requires little computational effort. The method covers a set of geometries that suffices to produce coherent models depicting typical structural and MEP systems.
We introduce our method and showcase its applicability through several stages in an experiment, as summarized in Figure 5: We start from a semantically segmented point cloud (b), produced from a raw laser scan point cloud (a) depicting the roof structure of a typical industrial scene. This data is then enriched to recover the underlying basic structure (d) and produce a semantic-geometric 3D model based on procedural geometries as the final model reconstruction result (e).

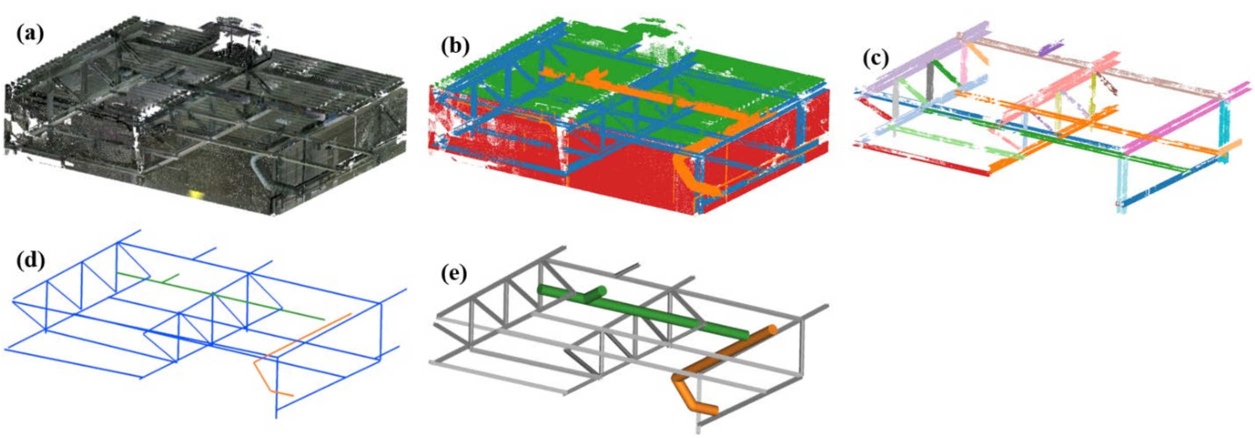

Figure 5: Stages of the Experiment: Original, colored point cloud (a), semantic segmentation results color-coded: wall, roof, beam, pipe (b), instance segmentation result (beams only) (c), refined recovered basic structure (beams, pipes) (d), and model reconstruction result (e).

The presented method can still be improved in terms of precision and robustness by finding more precise methods for segment identification and reconstruction than PCA and by extending it to allow for more different types of beams (T, L, etc.), ducts and more to build towards a robust solution applicable to real-world projects. Furthermore, the current implementation works solely on sweeping operations - the resulting model quality can be improved by avoiding object collisions and joining the geometries more realistically. The presented hierarchical refinement algorithm already ensures the required precision in the basic structure. While the method contains a new approach to building coherent systems of objects, it relies on the precondition that instances are correctly identified in the first place.
Overall this contribution adds to the body of knowledge with a set of methods for Scan-to-BIM to answer potential requirements with a high degree of automation - while the individual steps are based on reliable, well-proven techniques that lead to robust results.

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