State of research in Automatic As-Built Modelling

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ABSTRACT

Building Information Models (BIMs) are becoming the official standard in the construction industry for encoding, reusing, and exchanging information about structural assets. Automatically generating such representations for existing assets stirs up the interest of various industrial, academic, and governmental parties, as it is expected to have a high economic impact. The purpose of this paper is to provide a general overview of the as-built modelling process, with focus on the geometric modelling side. Relevant works from the Computer Vision, Geometry Processing, and Civil Engineering communities are presented and compared in terms of their potential to lead to automatic as-built modelling.

Keywords - Building Information Model (BIM); As-Built Modelling; As-Built BIM; As-Designed BIM

1 Introduction

Building Information Models (BIMs) are digital representations of facilities that encode all the relevant information about their life cycle from construction to demolition, including, but not limited to, 3D design drawings, schedule, material characteristics, costs, and safety specifications. Conceived using open standards to facilitate knowledge sharing and interoperability between different stakeholders, BIMs gained a general acceptance within the construction industry, as they are expected to provide significant cost savings and improved productivity in construction projects. Standards for BIM creation include (a) Industry Foundation classes IFC (ISO 16739) for building models, (b) ISO 15926 for process plants models, and (c) IFC-Bridge or BrIM for bridge models.

Whilst creating *as-designed BIM*s (i.e. BIMs generated in the design stage of a facility) is a straightforward process becoming increasingly common, generating *as-built BIM*s (i.e. BIMs that reflect a facility in its as-built conditions) is a challenging, but necessary process for facilities not equipped with an as-designed BIM and for facilities where the as-built conditions differ from the as-designed BIM. The focus of this paper is set on the as-built BIM (AB BIM) generation for buildings..

Creating an AB BIM requires two major steps: *data collection*, to capture the as-built conditions, and *data modelling*, to generate compact, but rich representations readily understandable by other processes. Although historically, (AD) BIMs were introduced in the 70's, gaps in technology (in data collection and storage) and knowledge (in data modelling) prevented the construction industry from employing AB BIMs; to this date, very few AB BIMs exist. Auspiciously, the 3D reconstruction field, related to Computer Vision and/or 3D laser scanning techniques, filled the technology gap, offering off-the-shelf tools for generating 3D models of scenes. Consisting, basically, of a set of 3D points endowed with 3D Cartesian coordinates and possibly colour information, these models that will be denoted from now on as *point clouds*, are useful for visualisation or augmented reality purposes [1]. However, the data modelling side continues to be deficient, and the problem of converting the raw point cloud into a semantically rich BIM model is far from being settled. Available commercial and academic tools to perform this conversion require extensive human intervention, making them expensive and error-prone [2]. Given the expected economic impact, automatically generating AB BIMs from point clouds is a key objective for the industrial, academic, and governmental parties involved in the Architectural/Engineering/Construction and Facility Management industry (AEC/FM).

This paper provides a general overview of the as-built modelling process, with focus on the data modelling side, and presents relevant works from different research communities, discussing their potential of being used to automatically generate AB BIMs from raw point clouds of buildings. Whilst AD BIMs, if present, can greatly facilitate the modelling process, in this work we limit the discussion to as built modelling in the absence of AD BIMs. We refer the reader to [46] for a more general discussion on as built modelling, including as built modelling of industrial plants.

2 Problem Statement

Given as input a raw point cloud, the goal of the as-built modelling process is to generate a semantically rich 3D model of the facility, composed of objects characterised by *geometry*, *relations* and *attributes* [3]. Ideally, the result would be an AB BIM file, encoded using a standard language, e.g. IFC in the case of buildings.

Preliminarily, it is worth noting that the as-built modelling process is limited by several *objective* factors, and thus even the best possible as-built modelling method cannot be expected to output an AB BIM as rich as an AD BIM. The following aspects, and possibly others, induce objective limitations in the as-built modelling process:

- AD BIMs contain semantic information pertaining to the designer's high level knowledge, but which cannot be (physically) inferred from a digital model, e.g. specifications, costs [4];
- The level of detail of the resulting AB BIM is limited by practical aspects related to data collection. Even if presumably the technology used for data collection is able to capture fine structures like outlets, or fasteners, the added-value of modelling these small elements does not justify the time and costs needed to meticulously collect and model the data [5];
- Non-visible and partially occluded building elements cannot be captured during data collection, hence they will not appear in the final AB BIM; e.g. the reinforcement inside a concrete column [6]. Note that devices to capture the non-visible elements exist (e.g. non-destructive testing technologies like ground penetrating radars), but research on automatically interpreting data coming from such devices is in very early stages, and no successful procedure is available to date, hence these devices will not be considered in this study.

Taking these limitations into account, we define the desired output of the as-built modelling process as a *working BIM* model, which represents a reduced version of the *complete BIM*, and encodes visible building and spatial elements, together with their relationships.

Using an object-based inheritance hierarchy, IFC defines three abstract concepts: object definitions, relationships, and property sets, whose sub-classes are used to define a BIM [7]. The working AB BIM is expected to contain visible objects encoded in IFC as instances of the IfcBuildingElement class (beam, chimney, column, door, wall etc.), and instances of IfcSpatialStructureElement (building, storey, site), but not IfcElementComponent (fastener, reinforcing mesh), or IfcDistributionElement; building elements also include information about material properties. Relation-wise, instances belonging to (at least) IfcRelDecomposes and IfcRelConnects need to be modelled, since the proximity and nesting relations of building elements can be captured from the as-built conditions, whereas higher-level semantic relations like IfcRelAssociatesConstraint which links a certain IfcConstraint object to a building element cannot be inferred.

The key task in generating the AB BIM described above is the recognition of the predefined building elements and their relationships. Note that in practice, generating the volumetric representations and the relationships of the predefined building elements suffices, as commercial tools to perform the conversion between a CAD model and IFC objects exist [8]. Depending on the approach, different auxiliary tasks can be used to facilitate this process:

- *Geometric primitive detection*: Report if and where predefined simple geometric shapes appear in the given point cloud, e.g. detect planar patches.
- *Point cloud clustering*: Given predefined criteria, e.g. planarity measure, cluster the input points to obtain segments of points with similar descriptors.
- *Shape fitting*: Given a subset of the original point cloud and a predefined model (e.g. a cylinder), find the parameters of the model.
- *Classification*: Given the segmented point cloud obtained above, assign to each segment a unique building element label.

Note that when an AD BIM is available, the sought output remains the same, but the tasks undertaken to achieve it shift their focus from detection and recognition to one-to-one matching and verification.

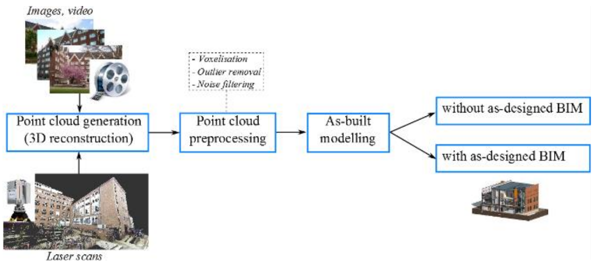

Figure 1 As-built modelling process

The general as-built modelling process, from data collection to BIM generation, is summarised in Figure 1, and comprises the following steps: point cloud generation, point cloud pre-processing, and as-built modelling per se. For self-containment, we first discuss briefly the former two steps, and then we address extensively the as-built modelling step. The aim is to give a critical analysis of the state of research, comparing the existing works in terms of the output they provide, and how close or far they are from the desired output. This will result in positioning the existing works in the space of possible outputs, governed by the objective limitations mentioned above and the intrinsic limitations of each method, as depicted in Figure 2.

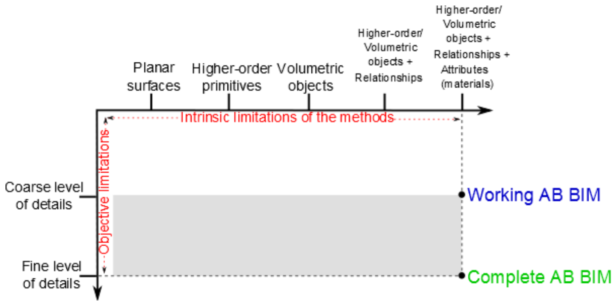

Figure 2 Output space of as-built modelling

3 As-Built Modelling from Point Clouds

Generating the full geometric model of a facility is an intricate problem, mainly because the point cloud to be processed is generally very large, and it contains a high number of infrastructure elements that need to be identified (e.g. walls, floors, windows), possibly in the presence of clutter. Detecting and recognising predefined infrastructure elements is the core of as-built modelling. However, of equal importance is the modelling of the relationships between elements, which can contribute in obtaining a coherent global geometric representation.

Depending on the criterion used to define this global coherency, existing approaches in geometric modelling can be classified into *global optimisation approaches* and *local heuristics*. The former are generally model-based, and reason about the scene as a whole, trying to find a global geometric interpretation that is optimal in terms of maximum a posteriori estimation [9], [10], [11] or energy minimisation [12]. The relationships between the elements can be used as an active ingredient of the global model, allowing to inject prior information about the scene layout [9], [11], e.g. common relationships are "adjacent walls are perpendicular to each other", "walls and floors are perpendicular", "doors are contained within walls", etc. Opposed to this holistic approach, which can be quite complex model-wise and expensive computation-wise, the local heuristic approaches use bottom-up reasoning, in which the elements of the scene are treated independently and possibly the prior information about the relationships between the elements is used as a rejection criterion for potentially erroneous local configurations [13], [14].

In both categories, there exist few works that describe full modelling procedures for point clouds, pertaining to Computer Vision, Geometry Processing, or Civil Engineering communities. But other works that address either particular parts of the as-built modelling, or the geometric modelling problem in general, are also of interest, hence they will be included as well in our discussion. However, we focus on automatic methods or works that have potential in the process of automatically obtaining BIM models; we do not detail works that depend on some form of user interaction; see e.g. [15] for a presentation of these works.

3.1 Global optimisation approaches

Dick et al. proposed an automatic framework for the geometric modelling of point clouds of buildings [9], whose output is a volumetric representation of the building, with objects labelled as "wall", "door", "window", "column" etc. Their approach uses a Bayesian model, whose overall prior distribution is obtained by modelling the prior distribution of each building element represented through simple parametric shapes, together with their relationships. At modelling time, a Markov Chain Monte Carlo (MCMC) algorithm is used to find the parameters of the building elements that maximise the a posteriori likelihood. A similar overall reasoning is used by Lafarge et al. for urban modelling [16]. The main strength of these works resides in the fact that they lead directly to a semantic interpretation of the scene objects, together with their relationships.

A natural possibility to exploit the prior information on relationships between elements is to use graphical models trained using labelled data, i.e. a segmented point cloud with elements labelled as "wall", "door", "clutter". Based on this idea, the authors of [10] train a Conditional Random Field to model the relationships between planar patches extracted from point clouds of buildings. Explicitly modelling the relationships between the elements of the scene improves the accuracy of the overall geometric modelling process. A different formulation based on graphical models is used in [11] for urban modelling. The authors start by semantically segmenting the point cloud into four different classes ("building", "vegetation", "ground" and "clutter") and minimise an energy functional to find an optimal configuration. The outcome is a combination of parametric shapes (planes, cylinders, spheres or cones) to describe regular roof sections, and mesh patches for irregular roofs. The compactness and the representation power of this approach make it appealing for modelling buildings in the presence of clutter. In a similar reasoning, but targeting indoor scenes, the authors of [17] first extract a coarse scene structure by semantic segmentation of pixels into "ground", "walls & ceiling", "furniture", "props", then use integer programming to obtain a refined optimal configuration of the scene, while considering support relationships between the elements of the scene. Again targeting indoor scenes, Bao et al. [18]

distinguish between (planar) surfaces that belong to the room layout and those that belong to objects in the room, by using cues from both the point cloud and the images, in a cost function minimisation problem that seeks to estimate the room's layout.

An integrated framework to model a scene as a set of interrelated networks of labels, functionalities, and descriptors, is proposed in [19]. Although it allows to reason about a scene at a very high semantic level, the framework has reduced flexibility in modelling the interactions between the networks; hence the contribution of this work is mostly at a theoretical level.

Although not specifically addressing the problem of semantic point cloud modelling, the works on geometric multi-model fitting proposed in [12] are relevant for as-built modelling. In both approaches the authors formulate a global energy minimisation problem that considers the multi-model geometric fitting as an optimal labelling, solved using graph cuts [20].

3.2 Local heuristics

Sacrificing the notion of statistical optimality, a large number of works related to as-built modelling consider local heuristics approaches, in order to obtain more efficient algorithms. Generally, these methods take advantage of the fact that the geometric model of a building can be fairly decomposed into simple parametric surfaces. The typical process starts by segmenting or clustering the point cloud using arbitrary criteria, and then fits different parametric shapes on the segments obtained. Strong cues specific to architecture scenes like orthogonality or symmetry, are typically used to guide the heuristic search, and discard abnormal configurations. Prior information about the layout of the buildings are used to attach semantic information to the detected elements.

More specifically, the authors of [21] assume that walls are orthogonal to the ground, and apply space sweep algorithm [22] to detect them. The same algorithm is used in [23] to recognise the planar structures of a room. In [13], the authors first automatically infer a coarse model of the scene, by detecting the planes associated to its principal directions. This coarse model guides the detection of more complex polyhedral objects, representing doors and windows.

In a series of papers, Stamos and Allen [24] seek to build textured geometric models from range scans and unregistered images. The two data sources are processed in parallel to extract 3D lines from range scans and 2D lines from images, which are then matched to obtain images-scans registration, needed to texture the 3D model. Using laser scans data, Wang and Cho detect boundaries as line segments and use them to identify roofs, windows, doors, and walls [25].

Closely related to the model-based approaches mentioned above, the method introduced in [26] for urban modelling uses graphs to encode the connectivity of planar elements, and recognise predefined configurations by subgraph matching. In [14], the authors extract planar patches, which are classified into semantic elements ("wall", "door", "window" etc.) using hard-coded prior knowledge. The result is a polyhedral model of the building. A similar approach is used in [27], where parametric primitives are detected using Hough transform, and described through their geometric characteristics (area, relative scale, planarity score etc.), which are used to identify openings' type and distinguish them from clutter by training an SVM classifier. In [28], planar patches previously extracted using a region growing algorithm, are classified using a stacked learning approach and contextual features. Similar to [27], openings are distinguished from occluded regions on a wall surface using SVM. In [29], the authors first detect planar surfaces and quadrics, which are then classified using multi-class AdaBoosted decision trees [30].

Targeting scenes containing only planar surfaces, Xiao and Furukawa [31] generate a textured CSG representation of a point cloud by processing 2D horizontal layers to get room layout hypotheses, which are then merged to obtain the 3D model using regularity constraints about the structure of the building. The authors of [2] adopt a robust approach based on RANSAC to detect walls as planar patches bounded by 3D lines, and then identify openings within walls.

In a more recent work [32], Poullis presents a full bottom-up framework for automatic modelling of urban point clouds, without any prior constraint on the elements types or their relationships. A hierarchical clustering through greedy region growing allows to segment the point cloud into surfaces, whose boundaries are determined using a graph-cut energy minimisation. The results on very large point clouds are impressive, proving that even simple local statistical reasoning can lead to robust techniques for point cloud segmentation and extraction of parametric primitives.

3.3 Auxiliary heuristics

This section describes heuristic geometric modelling works that do not provide a semantic interpretation of the scene, but which could be used as building blocks of the as-built modelling process.

Some authors addressed the problem of obtaining more compact representations of point clouds, while ignoring the semantic modelling. In this line of works, the authors of [33] detect parametric primitives (planes, cylinders, spheres) that replace the regular parts of the mesh, whereas the highly detailed parts of the mesh are kept as is. This strategy reduces the memory requirements, while preserving the distinctive features of the building. .

In [34], the authors address the planar patch extraction problem, and apply sparse subspace learning to cluster the points into linear subspaces [35], and then robustly fit planes [36] to each detected segment. In the same line of works, many versions of region growing algorithms have been proposed to extract planar patches from point clouds, by first clustering the points using some local measurements, and then fitting planes on the resulted clusters [37].

To fit higher-order parametric primitives to point cloud data, algebraic and iterative methods exist. Admitting a closed form solution, algebraic methods are efficient [29], but can have strong bias on incomplete data [38]. To obtain more accurate estimations, iterative methods are used which minimise a geometric error or an approximation of it [39]. The method proposed in [40] fits NURBS to pre-segmented point cloud parts, offering shape freedom and accounting for missing data. The point cloud segments can be obtained using a context free segmentation method, as the one described in [41], which employs a region growing algorithm based only on geometric properties.

Targeting the problem of robustly fitting multiple different geometric models to point cloud data, Schnabel et al. propose a RANSAC version based on a new sampling strategy together with an early termination scheme that provides a significant speedup [42]. Another approach for robustly fitting multiple geometric models, J-linkage, is proposed in [43]: each point is represented by its preference set, defined as the set of models that are satisfied by the point within a tolerance. By clustering points with similar preference sets, the point cloud is segmented and the underlying models retrieved. In the same line of works, Nurunnabi et al. [44] proposed the Diagnostic Robust PCA (DRPCA) to locally fit surfaces, obtaining improved performance compared to other methods based on PCA, MSAC and RANSAC; it accurately fits planes in the presence of outliers and calculates the local surface normal.

3.4 Overall analysis

The high diversity of the works presented in this paper in terms of application field, methodology, and goals, makes it difficult to conclude with an objective comparative analysis. Considering the problem statement enunciated in Section 2, we will position some of the main works discussed above in the output space of as-built modelling; the result is depicted in Figure 3. It can be readily observed that the majority of works concentrate on modelling planar surfaces along with their relationships. This is due, on the one hand, to the high frequency of planar elements encountered in building models, and on the other hand, to the reduced complexity of the problem; as soon as higher-order primitives are included in the analysis, non-trivial model selection issues occur. It is encouraging that few of the existing works reach volumetric representations and model inner relationships, getting close to the desired target. Among them, [29] and [27] are computationally more efficient. The missing link appears to be the material modelling, but since separate works on material modelling exist [45], including this step should be straightforward.

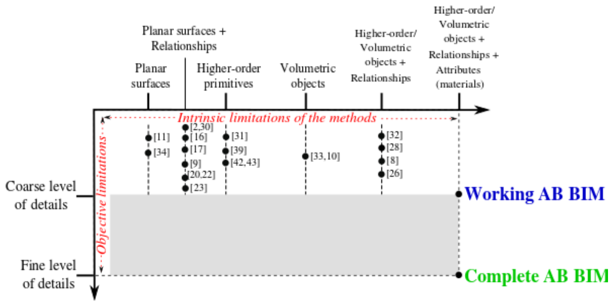

Figure 3 Existing works represented in the output space of as-built modelling

4 Conclusions

This paper gives an overview of the as-built modelling process, by presenting various research works from different research communities (Computer Vision, Geometry Processing, Civil Engineering) that are currently used, or have the potential of being used, for successfully solving the challenging task of automatic as-built BIM generation for infrastructure. Significant progress has been reported in the last years in this direction. While obtaining complete BIMs can engender high (unjustified) costs in practice, we believe that automatically generating working BIMs is achievable. For the future, the focus should be put on consolidating and integrating the existing techniques, along with developing new methods for object recognition. The recent advancements in object recognition and semantic segmentation [47] from the Computer Vision community using deep learning point to promising directions for automating object recognition tasks from point clouds. Joint research efforts within interdisciplinary projects can lead to accurate as-built BIM generation, producing a high impact in the construction industry.

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