A Review on Methods for Generating As-built Building Information Models

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Abstract

The use of as-built Building Information Models (AB-BIM) has dramatically increased over the past decade. Their use spans from visualisation to feasibility studies and from environmental analysis to refurbishment and maintenance. Currently, an AB-BIM is created by laser scanning a facility and manually modelling the acquired point cloud. The modelling process, however, is tedious and time consuming and necessitates experienced personnel. This paper presents an extensive literature synthesis on generating As-built BIMs. The literature survey showed that modelling can be automated through two distinctive steps: (a) object detection and (b) modelling, where each step is performed using different methods. This paper examines each step separately and divides it into subcategories based on the methods used. The review concludes that even though state-of-the-art methods have promising performance, they are focused mostly on restricted and simple scenarios, such as rectangular rooms. Therefore, limited progress has been achieved for more complicated facilities, where there is a high number of objects and occlusion. For those, no formal and/or universal approach exists.

Keywords: BIM, as-built, automation, modelling

1 Introduction

The construction industry has failed to incorporate digital technology to the expected level (Cabinet Office 2011), buildings older than 30 years have no digital data let alone 3D information. Nowadays only a small number of present buildings have Building Information Models (BIM). The state of practice in the construction industry uses mostly 2D Computer Aided Design (CAD) drawings for visualising the as-is conditions of a facility. The current manual process for creating as-built BIM models consists of four main steps: a) data collection (laser scans), b) point cloud registration, and c) geometric modelling and d) addition of supplementary information, such as topological relationships of the different objects and material specifications. A Trimble case study on a simple facility showed that 27 hours were spent on step c and 3 hours for steps a and b (Trimble 2014). The process of converting point clouds in semantically rich objects is considered to be tedious, error-prone and it requires experienced personnel. Most of the efforts needed to create a BIM are spent on the design of the model, which in the context of existing facilities, is the manual conversion of the point clouds to a 3D model. Additionally, each object present in the scene should be detected. How can this process be automated?

The overall objective of this paper is to present the current state of research in automating the as-built modelling process. The problem of generating AB-BIMs is of course wider, if we consider higher levels of detail and fully occluded objects. This is, however, future research and in this paper we only address issues of large/visible objects. In the second chapter the current state of practice is presented followed by the current state of research. The state of research is divided into two sections: a) object detection, which is the localisation and classification of the objects present in the point cloud and b) modelling in which points are converted into objects. The analysis and conclusions sections summarise the limitations of the current methods and highlights future research needs.

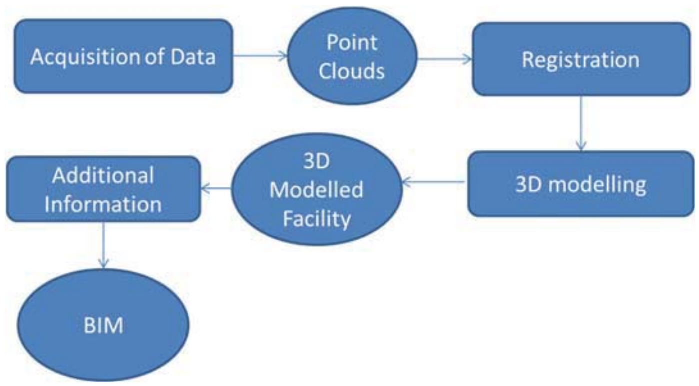

Figure 1 This figure presents the workflow for the creation of a geometric BIM from the acquisition of data up to the final geometric BIM (ellipses correspond to the input or output and squares to actions).

2 State of practice

Manual generation of as-built BIM Models can be performed with existing software including, but not limited to, Tekla BIM modelsight, Revit, and LFM. A generic method for the geometric modelling of a BIM for buildings and industrial facilities from point clouds is shown in Fig. 1. The user must first determine the category of the objects to be modelled. In the case of LFM Modeller the objects are classified into pipework, structure, and equipment. Then, a specific type of object to be modelled is selected; for example in the case of pipework, it is possible to select flanges, elbows, valves etc. The following step is to identify the object in the point cloud with the assistance of image data of the facility acquired with a laser scanner. Then, the boundaries of each object in the point cloud are defined; for example in the case of pipes, the beginning and the end points of the axis of the pipe are selected in the point cloud. Similarly for planar surfaces, its outline should be determined by selecting points along its boundary lines. Lastly, the selected object in question is automatically fitted to the corresponding points in the point cloud. The final output is a 3D geometric model where all elements have been modelled and labelled/classified.

A limitation of this procedure is that objects, in the point cloud, are not always fully visible from one view; therefore, it is needed to toggle between different views and scans to determine the correct boundary of the object. Also, as points seem to be scattered in the space, modellers can only roughly determine the boundaries, which sometimes leads to erroneous fittings. Therefore, trained modellers are needed.

The recently developed software called EdgeWise MEP can identify cylindrical objects in a point cloud and it can model them automatically. However, only cylindrical objects can be processed. The resulting model in this case consists only of geometrical solid bodies without each element classified.

A similar toolkit for AutoCAD is PointSense Plant. The user clicks along the pipe and the software automatically recognises patterns. In this case, points along the pipe are selected, in the point cloud, and the software automatically recognises the points that conform the pipe as well as other objects, such as elbows and gaskets. Even though different elements are classified, human manipulation is once again necessary. Lastly, the Scan to BIM (Imaginit) software assists with the structural element modelling. For example, the user can fit a wall object given manually-selected points that define the planar surface that corresponds to the wall.

3 State of Research

3.1 Object detection

Object detection in 3D point clouds is the identification of the elements present in a point cloud through matching, contextual, or feature extraction methods. This is done by learning the characteristics of the objects, such as orientation, size and geometrical features. The methods presented are a) Scan-vs-BIM, b) use of RFID tags, c) machine learning.

Bosche et al (2009) and Bosche & Haas (2008) have proposed a Scan-vs-BIM method which combines PCD (Point Cloud Data) and the 3D as-designed BIM of a building. The 3D BIM model is converted to a point cloud and by using fine registration (Bosche et al 2009), the two models are aligned and objects are identified from the as −planned PCD to the as− built point cloud. This method has also been applied for formwork and rebar identification for tracking construction progress (Turkan et al 2013). This method can be used to analyse the deviation from the original plan and to track current conditions by detecting objects. Although they offer promising results for object detection, they require an existing as-designed BIM model. Also, if an object is not modelled in the as-designed BIM model, it cannot be detected in the point cloud.

A method for classifying objects using Radio Frequency Identification (RFID) tags has been proposed (Valero et al 2012). RFID tags, placed on the surface of the different objects, contain useful descriptive information about the elements, which are later read using an RFID reader. Although this procedure can effectively recognise objects, the placement of RFID tags on all possible items in large complex facilities like manufacturing plants can be tedious and time consuming. This approach requires supplementary equipment (RFID reader) to obtain the object information.

Another type of information that can be used are either (i) contextual relationships between objects or (ii) the shape, colour or other feature descriptors extracted from a dataset of objects. This is done to create a database of profiles. This labelled training data is later used on testing data in order to classify objects. There are a number of machine learning methods which have been used for detection in point clouds, such as Support Vector Machines (Himmelsbach et al 2009), Decision Trees (Ducic et al 2006, Zhang et al 2014) and Random Forests (Guo et al 2011). Other methods which have been used are the graphical models (Xiong et al 2013, Anguelov et al 2005). Further details regarding the implementation of supervised algorithms can be found here (Bishop 2006, Murphy 2012).

The first step to detection is training information that describe the objects. Detection of objects by using contextual information as prior knowledge has been proposed (Huber et al 2011, Adan & Huber 2011). Xiong et al (2013) proposed the creation of semantically rich 3D models by exploiting a number of local features. Such as orientation, area and height of planar patches, and simple contextual information that are present in interior environments. For example, the detection of an opening determines that the recognised planar surface on which the opening lies is a wall. The method defines four types of object models walls, floors, ceilings and clutter. The accuracy of correctly classified objects is 90%. The advantage, of this method, is that even objects that are geometrically similar and difficult to distinguish, can still be differentiated. These methods consider that building objects can be represented as parts that correspond to geometric primitives and have steady spatial relationships such as orthogonality, parallelism, and coplanarity. Also, they only address coarse structural elements and not interior objects. For the above reasons, in unknown environments and point clouds with multiple objects, the accuracy decreases. Another approach that uses contextual rules is the one developed by Pu and Vosselman (2009). In this case the point cloud is segmented to clusters and then the size, position, orientation, topology and point density are used to infer the class of the object. Son et al (2013) proposed to model and to classify industrial equipment using as pre-knowledge, topological relations (e.g. connectivity of pipes) and scene and geometric information (e.g. dimensions of the objects). The authors had prior knowledge of the type of the existing objects in the scene in question, their contextual relationships, and their number and sizes. In this case, modelling the pipeline can be achieved in a consistent and easy manner, but pre-knowledge of this information in each laser-scanned facility is not always available.

Another approach in computer vision and robotics for detection of objects is the use of features extracted from training data. Shape descriptors are features used to match objects in a scene by comparing them with a set of objects that are stored in a library. First the description of the shape of the different objects in the point cloud is computed and then the descriptor is inserted to a classifier. Shape descriptors are categorised into two classes, i.e. local and global descriptors. Local descriptors are based on the geometric properties around a point, whereas, global descriptors calculate a universal representation for each object in question. Examples of local shape descriptors are spin images (Johnson & Hebert 1999) and Point Feature Histograms (PFH) (Rusu et al 2008a), which define a support region around the points and then compute a histogram centred at that point. A global descriptor is the Viewpoint Feature Histogram (VFH) (Rusu et al 2010), which is a histogram representation of the distribution of the surface normal. Similar descriptors have been used for recognising objects in cluttered interior scenes (Rusu et al 2008b) and vehicles (Frome et al 2004) in laser scan data. An evaluation of a number of shape descriptors was performed by Alexandre (2012), showing that the descriptors which take into consideration colour information give the best detection results. However, colour cannot always be used as same objects might have different colour. Furthermore, a shape descriptor should be fast to compute, invariant to rotational changes, able to discriminate between similar shapes, be storage efficient, and be robust to partially viewed objects (Iyer et al 2005). Local shape descriptors have large computation times and they are not storage efficient due to the point-to-point computation of the geometric properties. A global shape descriptor that has been proposed satisfying the above requirements is harmonic shape histograms (Kazhdan et al 2003). It has been tested on exterior point clouds and compared to other features for the detection of trees, cars, poles and walls (Douillard et al 2014). It offered the second highest accuracy for each item, approximately 84% and 0.8 sec feature computation time. In contrast, the most accurate descriptor, Spin Images, gave a detection accuracy of 92% with a computation time ranging from 5.5 min to 11 min for each object. This computational time is prohibitive for large point clouds. Also, the Harmonic Shape Histogram was tested on a large scale object dataset, giving the highest accuracy for a single descriptor of 59.8% (Fehr & Burkhardt 2007).

Further research on supervised learning for PCD using a feature based approach has been conducted for detection of mouldings surrounding doorways and windows (Valero et al 2011). The region of interest is defined and then a 2D profile of the object is compared to 2D drawings of mouldings stored in a database. The aforementioned method, however, fails to distinguish between multiple objects and it focuses on one element only. Also, the use of a 2D profile discards important information. Furthermore, a single object detection on facades using images has been proposed (Reznik & Mayer 2007, Reznik & Mayer 2008). In this case, a sequence of images of the facade is used to reconstruct the facade and to recognise the windows by matching them with a manually constructed window image database. This finally enables the identification of the position and dimensions of the object in the PCD. Detection of elements of bridges (Zhang et al 2014) has been explored and may have significant potential. In this case, the detection of the objects was based on multiple features, such as primitive types, the normal vector of primitives and neighbouring statistics.

Lastly, research on object recognition on PCD has also found applications in robotics (Koppula et al 2011, Anand et al 2012, Gould et al 2008, Quigley et al 2009), which intends to increase scene understanding for robots and eventually better indoor navigation and object grasping. The method developed by Koppula et al (2011) was evaluated using features extracted from images and point clouds acquired through Kinect, as well as the use of contextual information. It showed that when all three cases are taken into consideration the accuracy of the detection is increased. Note that the precision of the detection results ranged from roughly 36%, using only features from images, to 65%, using shape information, to 81% when shape and image features (e.g. colour) were used along with contextual information. Even though, this research is not related to 3D modelling and civil engineering, it offers promising results.

3.2 3D Modelling

AB-BIM does not require only the detection of objects in the point cloud but these points belonging to the corresponding objects should be converted into 3D elements. The approaches to modelling can be distinguished in three broad categories: a) mesh triangulation without prior information, b) primitive modelling, and c) volumetric fitting.

Early work focused mostly on simple modelling of surfaces from point clouds. This is considered as the rough step to modelling arbitrary 3D points (Farin 1996, Stamos et al 2006, Frueh et al 2005, Furukawa et al 2009). This method deduces the topology of unknown surfaces by using edges and vertices to create triangles between three points (Stamos et al 2006) and to represent the surface of the structure. Mesh techniques allow the conversion of an unorganised point cloud into a continuous mesh. For example, Frueh et al (2005) used laser scan acquired point clouds of building facades and it was able to distinguish the foreground from the background. Then, texture was mapped from images onto the points and finally the triangulation of points followed. Although, this method is highly automated, it fails to give realistic results as finer details are suppressed. Furthermore, description of the surfaces is not provided thus there is no usable information regarding the surface representation.

Primitive modelling requires the extraction of primitives in a segmentation process. Modelling of planar surfaces by mapping them on 2D planes has been proposed (Pu & Vosselman 2009). Verma et al (2006) detected roof planar surfaces and modelled them by fitting a plane on the points and adjusting it by using the normal of the surface. However, a complete BIM should represent as volumetric primitives and not as simple planar surfaces. For more complicated primitives, such as tori and cylinders, the modelling can be achieved by sweeping a shape along a trajectory (Bauer & Polthier 2009). However, since model fitting is guided by the surface normal, these approaches cannot cope with noisy point cloud data. Furthermore, modelling by fitting CAD models to volumetric representations of objects has been proposed (Xiao & Furukawa 2012, Rabbani & Heuvel 2004). These methods use Constructive Solid Geometry (CSG). CSG is an intelligent explicit representation of objects consisting of complex shapes, which are combined with simple volumetric primitives such as cylinders and cuboids. Xiao & Furukawa (2012) proposed this method for interior modelling. In this case, the individual planar surfaces, such as walls, are not modelled separately, but a set of walls are modelled as cubes. This method assumes that the geometry of the building can be expressed as a cuboid, as long as the planar surfaces are either perfectly horizontal or vertical. Hence, these approaches are strictly restricted to rectangular shapes. Lastly, Rabbani and Heuvel (2004) proposed iterative algorithms to properly fit CSG into point clouds. The user selects the CSG that corresponds to a point cluster and then one of the iterative algorithms automatically fits the model to the cluster.

4 Analysis

Fig 2. categorizes the papers based on the detection process, the objects that the method was tested on and finally each shape corresponds to a modelling method. Current research has focused either on simple modelling of point cloud data or on expanding semantic representation of objects. In the case of simple modelling of the facilities, researchers focused on converting point clouds into consistent surfaces. As explained previously, the mesh methods, which have been used do not implicitly model the surfaces. This means that they do not provide information regarding the surface representation. This leads to unclear identification of individual components or the adequate representation of the as-is conditions. This fails to address the objective of using a BIM model where information such as the present objects are included. Also, primitive modelling and model fitting have focused on buildings composed of planar surfaces, i.e. facades or rectangular rooms. Whereas, in the case of modelling more complicated surfaces, the methods require manual input, they are computationally expensive, or they are not robust to noisy data in the point cloud.

In the case where use of prior information is used, the analysis of the literature shows that spatial relationships have been used for the recognition of coarse objects in rooms and industrial equipment. The limitations of these methods are that either information regarding the exact number and type of objects should be provided or they have been used in restricted scenarios. Shape descriptors have been used for class labelling in interiors. Although, these descriptors give promising results, the challenge of constant presence of partially viewed objects still remains. Considering the above limitations, there are no robust methods for automated detection of 3D representations that will systemise modelling of point clouds in complicated environments.

5 Conclusions

The problem in obtaining BIMs for existing facilities lies in the 3D modelling of point clouds which is critical to the creation of a visually rich and informative model. The state of practice up until now is limited to the use of software where the process of converting the point cloud data to 3D models is manual. Meanwhile, BIMs are not just a simple 3D presentation of the as-is condition of a building, something that can easily be achieved with the existing CAD technology. Instead BIMs should include components which are described by their attributes and relational information. Hence, a facility's BIM cannot be confined to the representation of the structure of the building, i.e. walls, floors, ceilings and openings. The clutter and the vast number of objects which are widely developed within a facility, increase the difficulty and add one more challenge to the existing problem. One of the biggest issues with object detection is that there are objects with similar characteristics. Also, objects can be partially viewed by the laser scanner and point clouds can contain noise.

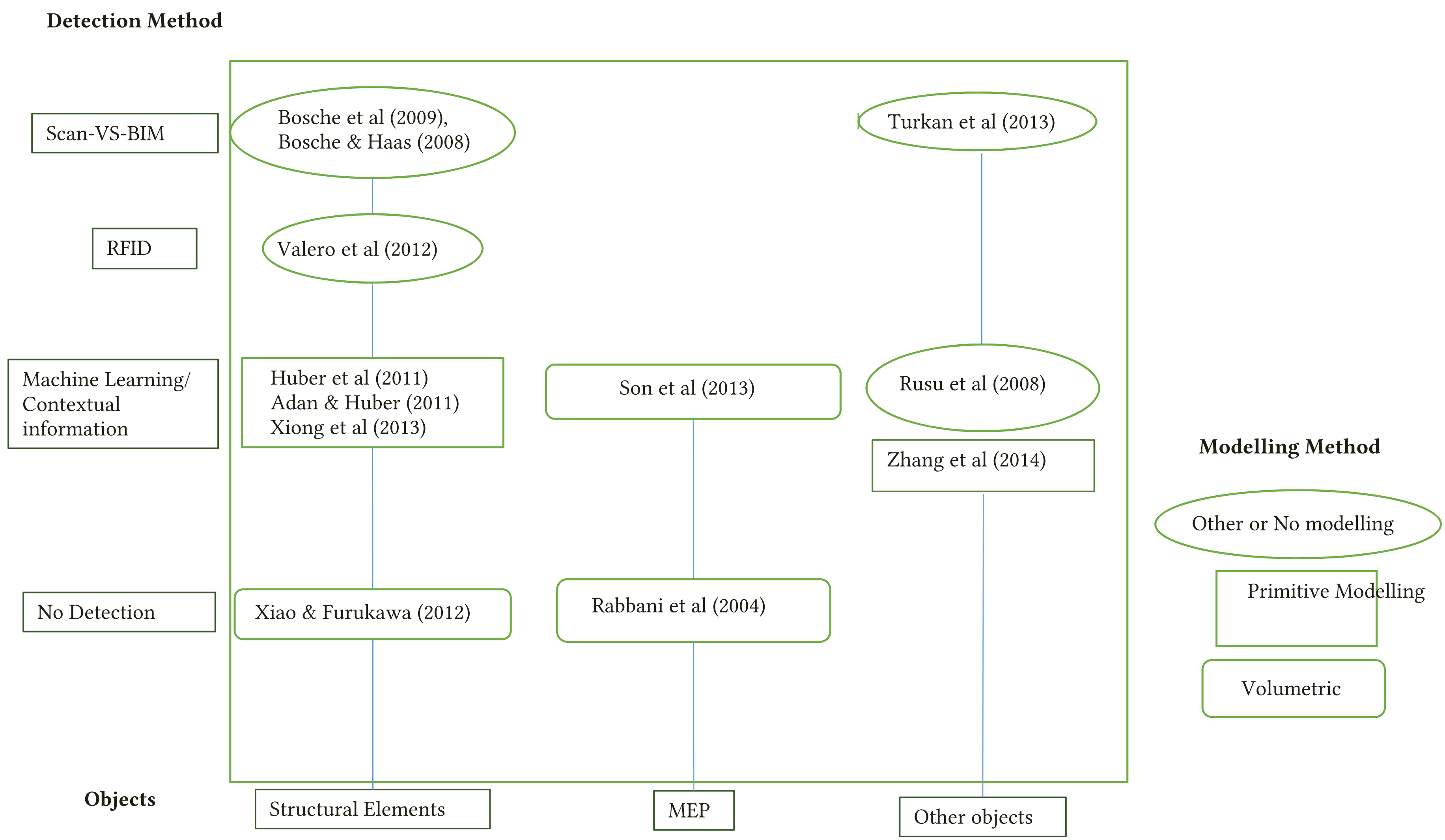

Figure 2 Presentation of Literature based on the detection method, the objects classified and the modelling method

Even though as-built BIMs could have significantly assist facility management and remodelling of facilities, the limitations imposed by the commercial software have hindered their use. This paper has presented the current state of research. Methods that have been explored for the detection of objects in point clouds and modelling of the objects have been reviewed. However, there are still major challenges to be addressed.

Research has to focus on developing a complete novel framework for the automation. On one hand, limited human intervention should be required so that the task becomes less error-prone and time consuming. On the other hand, all major objects which are frequently found in a facility should be correctly classified. Some of the underlined challenges in this procedure are the presence of occlusions, which leads to partially viewed objects, the number of objects present and the similarities in their shapes. Challenges that eventually affect the accuracy and computational efficiency of the algorithms. Although, research has just started on this topic, there are computer vision and machine learning algorithms having been developed in the past two decades than can tackle the issues leading eventually to the desired outcome.

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