Scan-to-BIM: Unlocking current limitations through Artificial Intelligence

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Abstract -

This paper discusses the current methods of Scan-to-BIM, a process which allows creating a digital representation of existing buildings for a planning methodology called Building Information Modeling (BIM). The study covers all stages of the process, from point cloud generation and pre-processing to BIM modeling and formatting. We review the work already done in this area both conventionally and with the addition of Artificial Intelligence approaches which have significantly improved the efficiency and accuracy of the process. With a particular focus on Artificial Intelligence, we explore how these advanced technologies transform and optimize every step, offering innovative insights and significant improvements over conventional methods. Through this investigation, we aim to provide insights into the capabilities and constraints of the Scan-to-BIM workflow, and to shed light on academic advancements and industrial perspectives.

Keywords -

AEC, BIM, 3D Scan, Scan-to-BIM, 3D Point Cloud, Artificial Intelligence

1 Introduction

In the Architecture, Engineering, and Construction industries (AEC), Building Information Modeling (BIM) relates to the creation of a digital representation of physical and functional characteristics of a building. BIM accelerates the digital transformation as a knowledge-sharing, collaborative platform among all stakeholders throughout the entire building life cycle. Over the last two decades, the adoption of BIM for building projects has been continuously growing thanks to many advantages and opportunities using the approach, such as automatic quantity estimation, swift responses to design changes, improved construction schedule visualization, and enhanced design coordination [1]. However, the implementation of BIM for existing buildings presents significant challenges. The primary issues encompass (1) technological, (2) financial, (3) managerial, (4) social, and (5) legal aspects [2].

One promising way to address the challenges associated with BIM for existing structures is the concept of Scan-to-BIM. Scan-to-BIM streamlines the process of gathering real-world data and converting it into a BIM-ready format. By capitalizing on advanced technologies such as laser scanning and photogrammetry, it eliminates the need for time-consuming manual data collection, ensures up-to-date information and reduces the associated costs.

Although already successfully applied in industrial use cases, Scan-to-BIM remains at the heart of current research due to many challenges such as manual intervention, lack of interoperability, algorithmic demands, technological limitations and the significant cost of these solutions [3][4][5]. Research has been intensifying with the recent integration of Artificial Intelligence (AI) approaches, thanks to their ability to speed up the process and even to remove some of the barriers by simplifying the processing steps [6][7][8]. However, there are still a considerable number of obstacles to be overcome before the process can be fully automated at both academic and industrial levels.

In this context, our paper presents a short and comprehensive state of the art on the Scan-to-BIM workflow, by inspecting its different stages and providing insight into their capabilities and current challenges integrating AI technologies. We highlight the advances made in the academic world and the state of industry through the scope of the general contractor Bouygues Construction.

2 State-of-Art

To conduct this state-of-the-art review, we analyzed 106 scientific papers that contribute to the body of knowledge surrounding Scan-to-BIM through all the stages of the process. The review was guided by the following top five keywords: ”Point Cloud”, ”BIM”, ”Artificial Intelligence”, ”Laser Scanning”, and ”3D Reconstruction”. These keywords were instrumental in filtering the vast

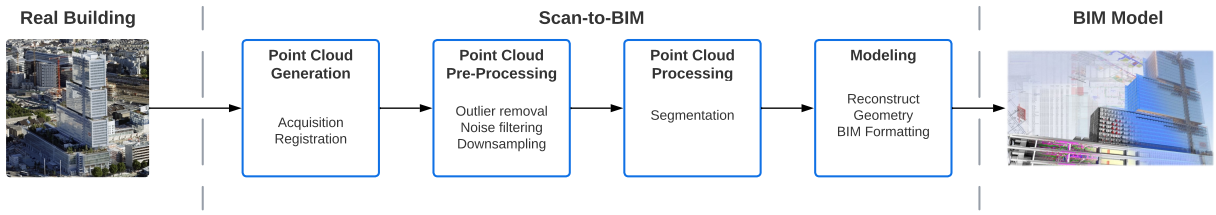

Figure 1. Scan-to-BIM differents steps

array of literature to focus on the most relevant and impactful studies in the field. A first observation is the gap between purely academic papers and those involving an industrialist in the field. In fact, in our review only 21 papers indicated that they had been written in partnership with industry or had received industrial funding. Most of these were software companies and not necessarily specialized in the construction field.

The Scan-To-BIM process represents the set of operations required to obtain a BIM model, and is now well defined in the literature. The process can be segmented into (1) generating the point Cloud from the existing structure, (2) pre-processing the data, and (3) creating the model [3][9]. Furthermore, these stages can themselves be further divided, as shown in `figure` 1, including steps like data acquisition and registration for the first, various filtering algorithms for the second, and geometry modeling, or link assignment for the last stage [10]. However, not all of these steps are equivalent in terms of complexity and know-how, and some of them are currently the subject of in-depth research.

2.1 Point Cloud generation

The first essential step in creating a BIM model consists in collecting accurate data from the existing structure. Several methods are commonly employed for this purpose, but the two main ones are photogrammetry and lasergrammetry, which result in a set of point clouds representing the geometry of the capture [9]. Photogrammetry is often favored for its speed and cost-effectiveness, while laser scanning, particularly terrestrial laser scanning (TLS), excels in delivering high accuracy [3][11]. It is however important to note that these observations are subject to change due to the rapid evolution of equipment in this field.

Laser scanning encompasses various categories, including terrestrial laser scanning (TLS), mobile laser scanning (MLS), and airborne laser scanning (ALS), each of them offering specific advantages. For instance, TLS is ideal for capturing large areas, whereas ALS is preferable for large-scale data acquisition. A number of scanning solutions for each category are already available on the market from companies such as Trimble, Faro and Leica. The last brand offers all three types of scanner, namely BLK360 (TLS), BLK2GO (MLS), and BLK2FLY (ALS) [12]. The choice may depend on the typology of the building and the given accuracy requirements [13].

The subsequent step is registration. This operation involves the alignment of point cloud scans taken at different stations, and their assembly into a unique point cloud. Some studies use the AI possibility to enhance this part and make it more efficient and quicker by reducing the time and resources used by identifying and eliminating noisy points [14] or improving position matching [15]. Beyond the academic research, the registration is often integrated into the software solution by the editing companies because it's important for industry to have a complete sequence from the point cloud acquisition to the point cloud deliverable.

The file format used for point cloud is typically binary such as PCD (Point Cloud Library) or LAS. Alternatively it can be an ASCII format like XYZ, or a hybrid format containing both, such as E57 [3]. All formats allow for the storage of point information, images, as well as metadata like timestamps.

In industry, this stage is often mastered and readily applied. Companies do not hesitate to acquire point clouds by surveyors, specialized external service providers or on their own, to produce valuable data which can be used either for a full Scan-to-BIM or for simpler tasks such as comparison or visualization.

2.2 Point Cloud Pre-Processing

Once the point cloud is acquired, the raw data should be refined, compressed and simplified in order to reduce the following processing costs as illustrate in the `figure` 2. To do so, different algorithms have already been studied and suggested in the literature.

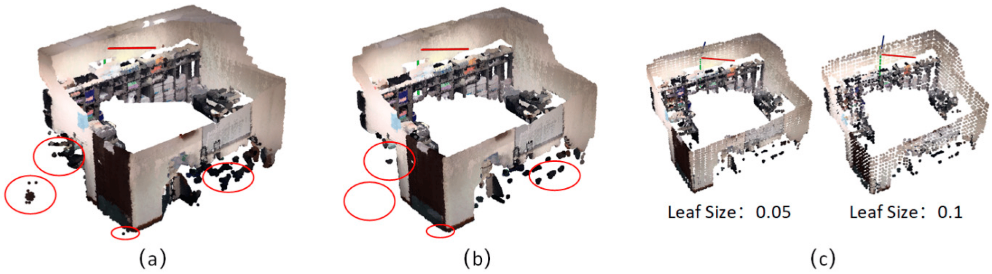

Figure 2. Pre-processing Filtering: (a) raw data, (b) outlier removal, (c) downsampling with different voxel sizes [16]

Outliers are data points that considerably deviate from the expected model, typically signifying errors or extreme values. Many algorithms and techniques have been developed to solve these issues. Traditional approaches dealing with outliers in point clouds include radius-based statistical suppression and mean-shift clustering [17] as well as the use of Z-scores with adaptive thresholds [18]. AI has also become increasingly important in outlier detection, thanks to statistical approaches based on density, clustering, learning and ensemble methods [19]. PointCleanNet uses deep neural networks to identify outliers and noise, and corrects them to preserve essential surface details, demonstrating remarkable efficiency even in dense and varied point clouds [20].

Noise can be described as erratic fluctuations in the data, often originating from measuring inaccuracies or other stochastic factors. To mitigate noise, Edge-Aware filtering or Bilateral filtering can be applied, as well as more recent approaches such as a high-performance algorithm preserving sharp features [21]. The use of AI, notably through approaches such as PointCleanNet, has marked a significant advance in denoising. Moreover, recent studies, including one introducing graph-convolutional representations [22] and local surface estimation via a deep neural network [23], show how AI can improve the accuracy and efficiency of denoising, effectively tackling even complex structured noise.

Downsampling is crucial for reducing data volume and facilitating further processing. Different approaches, such as voxelization, subdivide three-dimensional space into cubes (voxels), enabling a discrete representation of 3D points as volumetric data [24][25]. Although these methods have been widely used to simplify point clouds, they can lead to a loss of precision and data, limiting their effectiveness in demanding applications [26]. The introduction of AI into the field of downsampling has marked a turning point, with the development of sophisticated techniques capable of dynamically adapting the data reduction process while preserving essential features for downstream tasks [8]. Recent studies illustrate important progress in this field by evaluating different downsampling strategies such as 3D Edge-Preserving Sampling (3DEPS) [27], and by introducing frameworks capable of handling arbitrary cloud point sizes [28].

2.3 Point Cloud Processing

Segmentation plays a crucial role for Scan-to-BIM in order to classify and distinguish building elements such as walls, openings and floors. This process is crucial for the transformation of the scanned data to a high-level representation of the environment. In the previous steps, the algorithms did not differentiate between interior and exterior environments because they are the same type of data, but for the segmentation and modeling steps, these environments are treated differently. As a matter of fact, the treatment of the exterior (e.g. facade) or interior (e.g. room) will not be the same due to the different structural and architectural elements at different levels of complexity and involvement. Some algorithms such as RANSAC or similar methods are involved in the treatment of both typologies but employed differently.

In interior reconstruction, segmentation begins with the separation of floors, before moving on to delineating rooms, then walls and slabs, finally addressing the remaining elements if necessary [4]. This progressive approach is essential for establishing the overall geometry of a floor, advising that walls should be segmented first before rooms are defined [29]. A commonly employed method for floor segmentation is the use of z-histograms which generate horizontal slices of the interior space, facilitating the separation of the structure into individual floors [30]. This segmentation is followed by that of the rooms, which progresses from the base of the structure, i.e. the floor, and extends towards the elevations [31][32]. However, when reconstructing interior spaces, it is essential to take into account wall occlusions which can obstruct the view of certain elements. To overcome this challenge, specialized algorithms have been designed to deal with occluded elements, ensuring that no critical details are missed during the reconstruction process [33][34].

Exterior reconstruction follows a similar approach, segmenting buildings according to their relevant components: facades, roofs and ground surfaces. Facade segmentation, in particular, can be subdivided to improve information extraction, by dividing the facade into storeys, then into uniformly sized tiles, and finally into elements such as doors and windows [35]. Another approach considers the entire facade, using feature lines and cell complexes to determine division boundaries while addressing some occlusion issues [36]. In addition, segmentation of exterior point cloud can be achieved using images rather than scans, as demonstrated by contour and aperture detection methods [37][38].

The evolution of Machine Learning and Deep Learning represents a watershed in the efficiency of the Scan-to-BIM process, automating complex operations from occlusion detection to large-scale reconstruction. However, despite its transformative potential, Deep Learning faces challenges such as the need for manual design and heavy dependence on available data [6]. The contribution of Machine Learning to the field is illustrated by the improvement in semantic segmentation, in particular with the Random Forest (RF) algorithm, which led to the possibility of semantic segmentation [39], enabling precise recognition of building elements and automated generation of models based on predefined templates [40]. In the specific context of exterior facade analysis, Deep Learning applied to 2D orthoimages has facilitated automatic semantic segmentation, combining initial segmentation and 3D back-projection to obtain a semantically segmented point cloud. This method, although efficient, could benefit from images taken from more advantageous angles and the exploration of new data sources to improve overall accuracy [41]. At the heart of the innovations in 3D point cloud processing, PointNet and PointNet++ offer effective solutions to overcome the challenges of unstructured and disordered data (`figure` 3). By providing accurate segmentation and classification through a globally invariant representation, these algorithms play a key role in the detailed analysis of local features, essential for semantic segmentation [42][43].

Following these AI algorithms, more recent architectures such as Graph Convolutional Networks effectively exploit the graph structure of point cloud data to better capture local relationships [44]. Dynamic Graph CNN build a neighbourhood graph at each layer to capture richer local features [45]. PointCNN uses a convolution approach to learn a hierarchical representation of the data [46].

Figure 3. Example of PointNet classification [42]

Despite these new and promising algorithms, AI still needs to overcome a number of challenges, including the sheer amount of data required for training. Only few valuable training datasets such as S2DIS (Stanford 2D-3D-Semantics) [47], ScanNet [48] or Paris-Lille 3D [49] are publicly available. Current research is therefore turning to innovative approaches using synthetic point cloud generation in order to enrich the availability of varied and representative training data [50]. However, this type of method has its limits in terms of geometric representations, whether volumetric or in terms of detail accuracy. As discussed in [6], the success of Deep Learning highly depends on the relevance of its input data, and the use of small or synthetic data sets represents a major handicap for obtaining a stable solution.

As far as industry is concerned, some start-ups, companies and scanner publishers offer solutions based on artificial intelligence to process the point cloud and extract all the previous steps. However, this process has not yet reached maturity, and in most cases, these steps are performed manually, as they are considered more precise and important.

2.4 Modeling

The last step of the Scan-to-BIM process is the modeling into usable data such as 3D or BIM. The Level of Development (LOD) is an industry standard that defines among other things the degree of refinement for the 3D geometry of a BIM model shown in `figure` 4. LOD is an important key to completing Scan-to-BIM, as it defines the accuracy of detail required during acquisition and is a crucial input for obtaining a consistent BIM model.

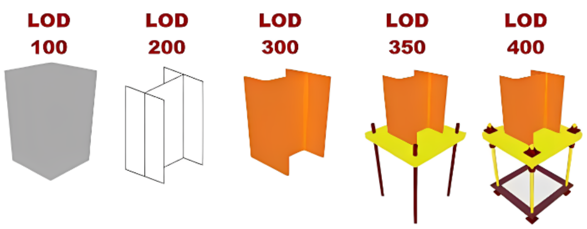

Figure 4. Example of LOD in a BIM model [51]

There are several different methods for obtaining a model from a point cloud that has been segmented and labelled. The first is parametric modeling, which offers great flexibility in the manipulation of architectural forms, particularly useful for facade renovation [52][53]. This approach emphasizes the importance of adaptability and reusability in the design process. On the other hand, semi-automatic methods combine human intervention with automation, enabling a balance between precision and adaptability [31] [54] [55]. These techniques aim to improve the classification and reconstruction of specific architectural elements, while offering superior geometric quality. Finally, full automation promises efficient creation of BIM and parametric 3D models, significantly reducing the time and effort required for modeling [33][56]. These approaches focus on accurate reconstruction of walls and their topology, and on optimizing the overall connectivity of interior spaces. These global methods use approaches that can be grouped into three categories: (1) planar primitive detection, (2) volumetric primitive, (3) mesh-based reconstruction [3].

The papers therefore typically focus on one type of typology such as exterior or interior, which corresponds to a specific industry use case. Also, the type of reconstruction will depend on the needs, as a mesh reconstruction will be less accurate than a full BIM, but quicker to obtain for elementary visualization. Modeling in industry is mainly done manually, using appropriate software such as Autocad Revit. This can be explained by the fact that existing algorithms are not yet mature enough, due to a lack of adaptability, and that industry, through its use cases, does not necessarily require a complete BIM model. For the integration of AI in this area, an important future approach could be the automation of repetitive tasks and the point cloud quality control, which will be an important issue in ensuring the accuracy of the data created through the Scan-to-BIM process.

3 Conclusion

The state-of-the-art analysis attests promising advancements in point cloud generation methods, pre-processing techniques, segmentation and 3D modeling approaches. Most literature on Scan-to-BIM targets finished structures or historic buildings, overlooking its potential in managing the construction phase. Applying Scan-to-BIM for monitoring work progress and as-built verification introduces new challenges in harnessing construction site data beyond traditional practices. Furthermore, only few work is dedicated to the overall Scan-to-BIM process. The different stages presented in `figure` 1 do not get the same amount of attention in the literature, which is understandable for a relatively mature stage such as data acquisition, but less so for BIM formatting, i.e. translating the 3D model to a BIM model. As a matter of fact, the challenges involved in producing a complete BIM model are different from those for creating a 3D geometry.

The Scan-to-BIM process needs to be improved to become a complete and automatic process. This includes addressing existing challenges such as occlusion and clutter in the point cloud [3], improving the AI in its design, its training, and in controlling the result [8], and implementing a complete path among all stages so that they are no longer independent. In addition, involving industry to provide data sets and test sites would significantly speed up the development.

The industry, through the example of Bouygues Construction, is currently not using the solutions proposed in the literature, for several reasons. The absence of readily usable off-the-shelf solutions capable of managing the entire process, and the lack of resources to engage themselves in research are major issues. It is important to recognize that complete solutions, even addressing only specific environments or building types would be preferable to the current manual methods. Our next work will therefore focus on the implementation of a complete Scan-to-BIM process for a particular use case, namely the facade in the context of energy renovation for French real estates.

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