A Scan-to-BIM Automation Paradigm for Digital Transformation in the AEC Industry

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Abstract

Building information modeling (BIM) plays the central role in the digital transformation of the architecture, engineering, and construction (AEC) industry. As-built BIM plays a vital role in quality control, construction progress tracking, and infrastructure maintenance. Scan-to-BIM is an effective way to obtain accurate as-built BIM. Although Scan-to-BIM is a current research hotspot, it still faces challenges such as low efficiency and limited applicability. To address these gaps, this study proposes a Scan-to-BIM automation system (SBASE). SBASE integrates a large-scale data-driven deep learning method to obtain semantic information of 3D point clouds and perform instance segmentation. BIM can be automatically generated through model matching and parametric modeling. SBASE effectively combines rule-based and learning-based methods to improve the accuracy and generalizability of the model. Tests were conducted on real building facilities in Hong Kong to verify the reliability of SBASE. The results show that our proposed method can be effectively applied to unstructured building scenarios and contribute to the development of digitalization in the AEC industry.

Keywords: Building Information Modeling (BIM); Scan-to-BIM; semantic segmentation; Point clouds.

1 Introduction

The digital transformation of the architecture, engineering, and construction (AEC) industry is a key development direction for smart construction. Building Information Modeling (BIM) is an important part of this change and plays a key role in quality control, construction progress tracking, and infrastructure maintenance [1,2]. However, in actual construction, changes in the assembly process or construction deviations may lead to substantial differences between the design BIM and the as-built BIM in the project. The existence of such differences brings additional costs and potential safety risks to maintenance during the building operation phase. Therefore, accurate and comprehensive as-built BIM is needed to effectively support the development of the AEC industry.

Traditional methods of collecting as-built BIM require a lot of manual involvement, which is a tedious and time-consuming task. Considering the rising labor costs, and driven by technological advancement and the growing demand for efficiency, this paradigm shift has led to the rapid development of scan-to-BIM technology. The process of scan-to-BIM involves measuring and reconstructing the existing state of a building to obtain its functional and physical characteristics [3]. The process relies on the use of light detection and ranging (LiDAR) to obtain millimeter-level three-dimensional (3D) point cloud data (PCD), combined with other advanced technologies such as deep learning to capture the geometric and semantic information of the building environment. Scan-to-BIM can also achieve efficient management of the entire life cycle of a building project through real-time updating and integration of field data. Although scan-to-BIM has been widely used in the AEC industry, it still faces the challenge of low automation and still requires a lot of manual intervention in the modeling process, making it difficult to exert its advantages in some specific scenarios [2,3].

This research proposes a scan-to-BIM automation system (SBASE) to address the challenges faced by existing research. SBASE uses data-driven deep learning technology to perform semantic segmentation and instance segmentation on 3D point clouds [4], thereby accurately and efficiently representing the site environment. SBASE integrates model matching and parametric modeling to achieve automatic construction of BIM models. By combining rule-based and learning-based methods, SBASE not only improves the accuracy of the generated model, but also enhances its generalization performance in various building scenarios.

The structure of this research is as follows: Section 2 presents a literature review on scan2BIM and related advanced algorithms. Section 3 introduces the process and technical details of the proposed SBASE method. Section 4 analyzes the results of a case study and provides a discussion. Finally, Section 5 concludes the paper and offers future perspectives.

2 Literature review

2.1 Rule-Based Method

The semantic information of 3D point clouds is necessary for the automated scan-to-BIM process. General architectural elements (AEs) are typically composed of parts with regular shapes, such as walls, floors, columns, and beams. Therefore, we can identify and extract target objects based on the geometric and spatial information of the 3D point clouds through algorithms. Based on the generalized random sample consensus (RANSAC), Schnabel et al. [5] implemented the detection of various 3D shapes, including spheres, cylinders, and cones. Methods based on centerlines [6] can employ 2D Hough transformations on sliced point clouds to identify pipes with predetermined dimensions. Sectional analysis can effectively detect mechanical, electrical, and plumbing (MEP) components [2]. Slicing methods and Gaussian spheres can be used to determine the primary direction of cylinders [7,8]. Despite the progress made in the aforementioned studies, the algorithms have limitations in identifying capabilities for some complex building structures, such as bends and T-shaped cross-sections.

2.2 Deep learning-based semantic segmentation

Traditional Scan-to-BIM approach necessitates significant manual labor in data processing, resulting in evident drawbacks such as low efficiency and high cost. The development of GPUs has facilitated the increasingly widespread application of deep learning-based semantic segmentation in practice. Charles et al. proposed PointNet [9], which can apply deep learning methods to process point cloud data. The global features extracted by PointNet can accomplish classification tasks effectively, but its local feature extraction capability is relatively weak, making it difficult to analyze complex scenes. PointNet++ [10] introduced a multi-level feature extraction structure, which can effectively address the issue of uneven point cloud density. F-PointNet [11] expanded the application of PointNet to 3D object detection, combining image information to obtain a prior search range, thus enhancing efficiency and accuracy.

By leveraging contrastive learning and scene context information, the annotation work can be reduced and efficient learning of 3D point cloud data can be achieved [12,13]. One challenge faced by deep learning-based 3D point cloud semantic segmentation is the limited generalization capability of pre-trained models. When using a pre-trained model in an unknown scene, it is difficult for the model to meet performance requirements without retraining or fine-tuning [14]. The complexity of scenes poses challenges for the automation of the scan-to-BIM process.

3 Methodology

The SBASE method proposed in this study effectively overcomes the limitations of conventional techniques, enhancing the automation level of Scan-to-BIM processes. Building upon semantic segmentation of 3D point cloud models, SBASE automatically generates BIM models of AEs, such as walls, floors, columns, and beams. For detailed BIM objects such as doors, windows, lighting, and Heating, Ventilation and Air Conditioning (HVAC), and furniture, instance segmentation serves as a foundation for matching these elements with BIM targets in a model library, ultimately generating interior BIM models. We have developed functional modules within Revit and the BlenderBIM plugin to facilitate improved user interaction experiences.

3.1 Overall pipeline of SBASE

The overall pipeline of the SBASE is illustrated in Figure 1. The process begins with the preprocessing of the acquired PCD. After applying noise reduction techniques and other operations to enhance data quality, the resulting dataset is used as the input for the system. We conduct semantic segmentation on the input data in step 1.1, which can realize auto-detection of groups based on point semantics and generating statistical information of individual objects.

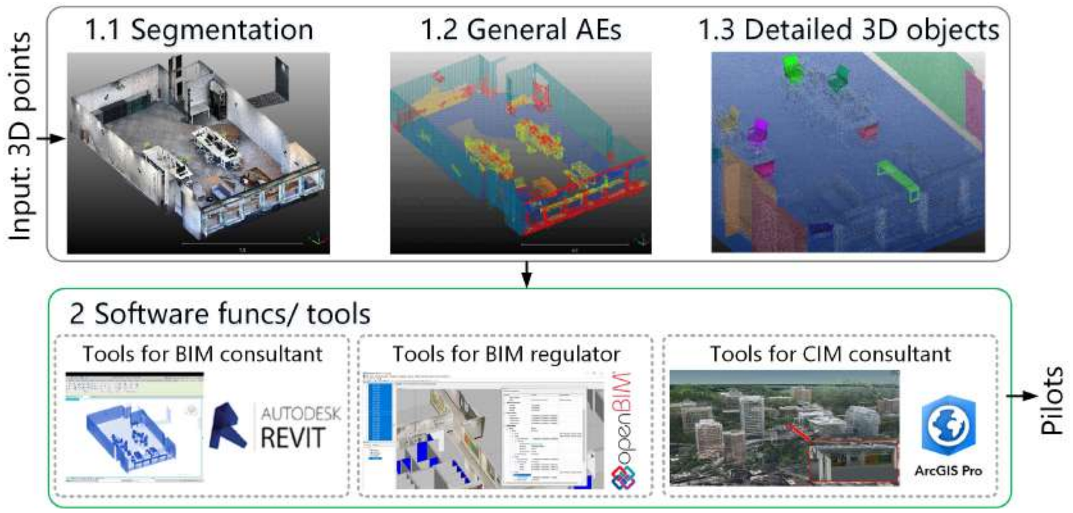

Figure 1. The overall pipeline of SBASE.

Step 1.2 focuses on identifying general AEs, including walls, floors, columns, and beams. This step involves filtering target objects and using object snapping to efficiently reconstruct building elements. The accuracy and reliability of general AEs are ensured by incorporating user input. Step 1.3 focuses primarily on the automation of detailed BIM object creation. The main goal of this phase is to automatically place “m” scanned objects in “n” BIM families, thereby simplifying the model generation process. In terms of software features and tools, the SBASE plugin provides strong support for commercial and open source BIM/CIM platforms, making it a universal solution for a variety of building and construction projects.

3.2 Algorithms and Data Flow

The proposed SBASE method combines spatial voxel-based room partitioning and Mask 3D for semantic segmentation, as shown in Fig. 2. To ensure the relevance and effectiveness of the algorithm in the local context, we prepared a training dataset specifically based on the needs of the Hong Kong building landscape. This includes the utilization of resources such as the Construction Industry Council (CIC) Public BIM Library, which includes a comprehensive collection of BIM families and types relevant to the region. By leveraging this tailored approach, our segmentation method can improve the accuracy and applicability of BIM models, ultimately contributing to improving the efficiency and reliability of the building planning and construction process.

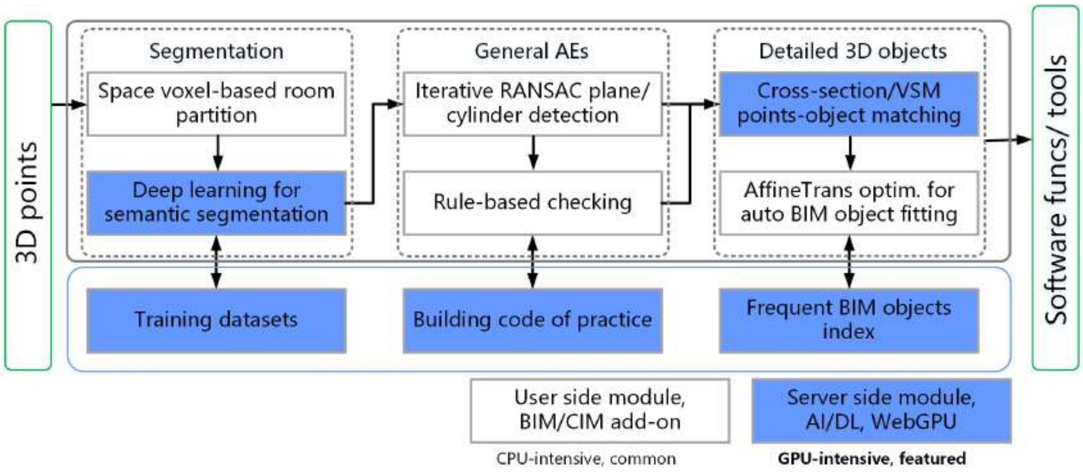

Figure 2. Algorithms and data flow.

To identify general AEs, we implement plane/cylinder detection based on RANSAC. By iteratively selecting random subsets of data points and fitting a geometric model, RANSAC is able to identify and distinguish various building elements in the point cloud, ultimately helping to generate accurate and reliable BIM models. We employ rule-based checks to ensure consistency with established architectural principles. Our approach follows the codes of building practice set by various departments. This compliance ensures that the generated BIM model meets the necessary legal and safety requirements and meets the highest industry standards.

We implemented affine transformation optimization for automatic fitting of BIM objects and frequent BIM object indexing. Cross-section and visual structural measurement (VSM) point object matching are used to associate 3D structures with predefined objects in the BIM model library, improving the accuracy of the model. Affine transformation optimization enables automatic fitting of BIM objects by rotating, scaling, and translating objects, reducing manual intervention and error rates. Frequent BIM object indexing improves query efficiency by sorting and indexing objects in the BIM model library.

4 Experimentation and Result

We developed a web interface for SBASE, which integrates functions such as user registration and project progress preview. This user-friendly interface enables seamless interaction between users and the system, facilitating efficient management of BIM projects, as shown in Fig. 3. In order to evaluate the effectiveness of the proposed SBASE method, we conducted practical tests and analysis based on real-world scenarios. PCD was collected within an office building in Hong Kong using a laser scanner, ensuring comprehensive coverage by setting up multiple stations at different locations. Subsequently, we registered the PCD and applied the proximity principle to fuse the acquired point clouds from various settings, ultimately generating a complete model of the office space.

Figure 3. The web interface for SBASE.

4.1 Case study

Figure 4 showcases the typical example results obtained using the SBASE method. For generic architectural elements, we employed RANSAC and rule-based checking to accurately derive BIM models of walls, floors, columns, and beams. By performing instance segmentation on the basis of 3D point clouds, we were able to swiftly and accurately obtain point clouds of object elements such as tables, chairs, and sofas. By matching the frequent BIM objects from the CIC and local objects with the point cloud models, we were able to obtain BIM models for different object instances. The results indicate that the Auto place by SBASE method achieved a precision of 0.8, recall of 0.857, and an F1 score of 0.828.

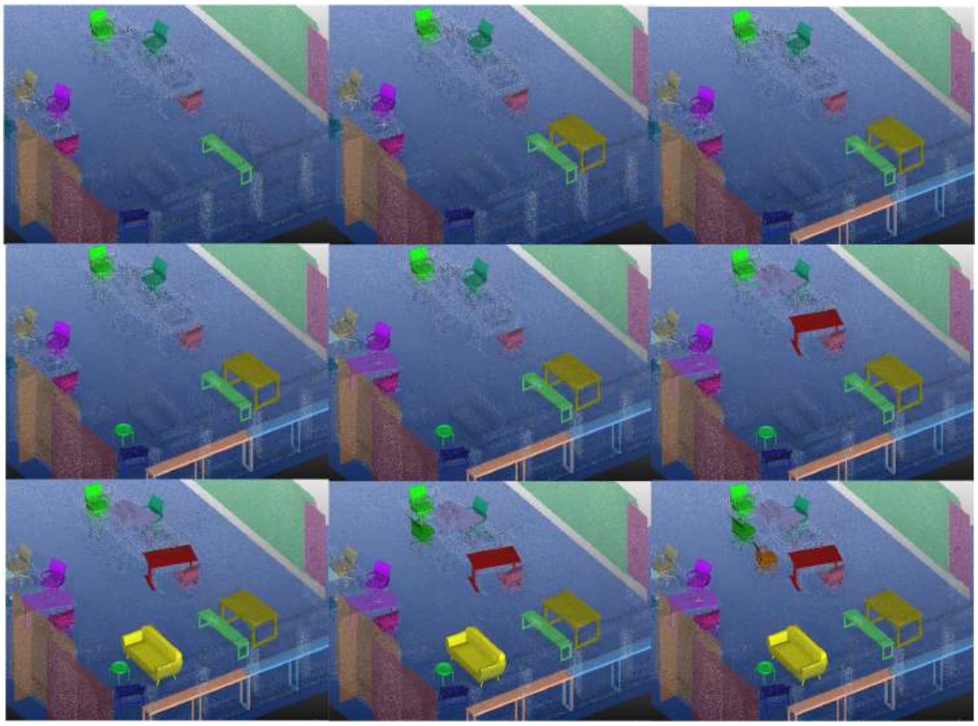

Figure 4. Results obtained by SBASE.

4.2 Discussion

We conducted a comparative analysis of different mainstream commercial software solutions and our proposed SBASE, as shown in Figure 5. In this context, PCD pre-processing refers to the file transfer process. The processing time for general AEs encompasses several stages, including room allocations and matching, measurement and deciding family type, placement of BIM families for walls and floors, and placement of BIM families for columns and beams. For detailed BIM objects, the processing time includes measurement and deciding family type, finding similar BIM families, creating new BIM families, and placing BIM families.

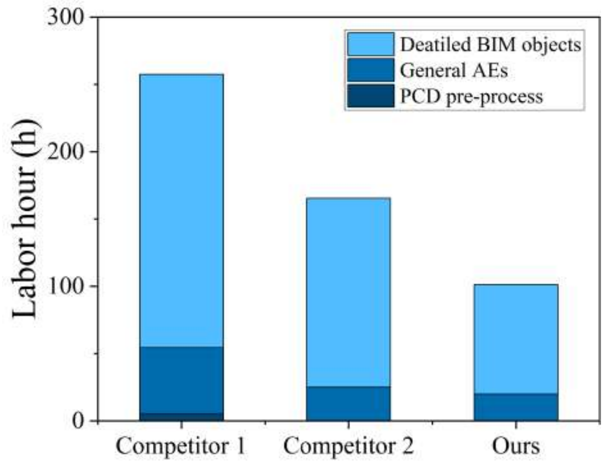

Figure 5. Comparative analysis of processing time.

The results demonstrate that the processing time required by the SBASE method is significantly shorter compared to its competitors, with time savings of 59.9% and 42.1%, respectively. The comparative analysis between SBASE and other commercial software solutions reveals the advantages of the proposed method in streamlining the BIM process and reducing processing time. This highlights the superiority of the proposed method in terms of efficiency and effectiveness.

5 Conclusion

The proposed SBASE method in this study is capable of integrating the advantages of both rule-based and learning-based methods, enhancing the level of automation in the scan-to-BIM process. The integration of a large-scale data-driven deep learning approach for semantic segmentation and instance segmentation of 3D point clouds within SBASE has shown to enhance both model accuracy and robustness. Tests on real-world building facilities in Hong Kong have demonstrated that SBASE, when compared to existing commercial software, achieves a notable improvement in time efficiency within architectural scenarios. Therefore, the proposed method holds substantial potential to contribute to the ongoing digitalization of the AEC industry. It is anticipated that future research and developments in scan-to-BIM will continue to leverage the advancements in deep learning techniques, further improving the accuracy, efficiency, and application of scan-to-BIM in the AEC industry.

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