An Integrated Solution for Automatic 3D Object-based Information Retrieval

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ABSTRACT

As-is building information model (BIM) is regarded as the mainstream solution of the digital twin (DT) for the intelligent building management, especially in the facilities management (FM) phase for the existing buildings. The current automatic scan-to-BIM methods mainly focus on the detailed geometric information modelling. However, the attributes information of the 'secondary' building objects is equally valuable comparing to that of the primary structural objects in the FM workflow. These components may include the light fixture, plumbing and heating terminal and furniture. The knowledge supporting to the FM practice can be extracted based on the geometric and attribute information. Therefore, the 'secondary' building components should be efficiently modelled as the main operation and maintenance targets in the FM phase. This paper proposes an automatic 'secondary' object-based BIM model retrieval method based on segmented point cloud model. The machine learning (ML) supported technical conceptual framework will be introduced in this paper.

INTRODUCTION

Point cloud data (PCD) currently serves as one of the primitive representations to aid in information modelling of existing building assets. Numerous researchers have developed the integrated solutions to convert PCD into the DT model. However, the current methods predominately focus on the geometric information modelling leading to that the value of DTs cannot be realised. The attached real-world attribute information attached is more important in the FM applications, such as operation and maintenance (O&M) management, asset management and energy management (Lu et al., 2020; Wen et al., 2020). There is rare research discusses about how to link the real-world building information to the created DT to facilitate its practical value. This leads to a significant gap for practitioners in utilising the constructed DT via the existing methods due to lack of knowledge output beyond geometric information. To address the challenge, this paper proposes an object-based ‘secondary’ building componence information retrieval method based on the BIM object libraries as key training datasets.

Unlike structural components, these 'secondary' components (Adán et al., 2018), for example, the attributes of lighting fixtures are useful for the energy consumption calculations. The BIM object databases are designed to include with these valuable attribute information as well as the geometric information to meet the multiple management requirements in the FM phase. By matching PCD with BIM objects, we can add valuable practical to enrich the DT model. Zeng et al. (2020) developed a user exemplar-based method method to create a query object and retrieve matching instances based on metric learning, and Adán et al. (2018) developed a DT reconstruction method using an object database. However, it is still a manual process to identify and match the corresponding digital object. The objective of this paper is to develop an integrated object-driven geometric and attribute information retrieval framework to realise the automatic knowledge modelling of DT. It leads to the research question of how to realise the object-driven information retrieval based on the collected PCD. The contribution of this research is to build the conceptual building information retrieval framework to enhance the practical value of as-is DTs. The other contribution is the integrated neural network to automatically identify the corresponding BIM object matching with the PCD cluster.

METHODOLOGY

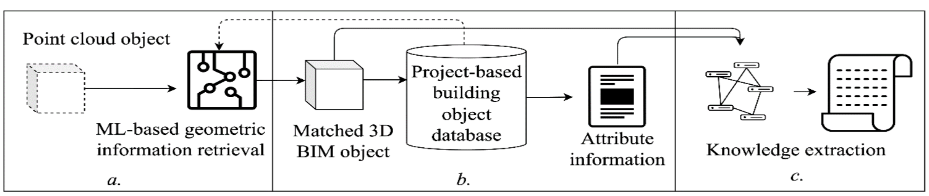

Figure 1 Research methodology

There are three steps involved in this framework (see Figure 1), which are: a. geometric information retrieval; b. attribute information retrieval; and c. knowledge extraction. The first step involves using a ML-based network to retrieve geometric information, which is the foundational stage where the shape and dimensions of the building are identified and captured. Once the corresponding BIM object is matched, its associated attribute information is retrieved. The attribute information matching in the next step mainly depends on a project building object database. It is crucial that the geometric and attribute information are already paired and stored, typically by estate management or an equivalent department. Finally, the geometric and attribute information will be function-centred organised in the ontology-based knowledge graph to significantly improves the practical application of the DT from the point cloud data. In this paper, the technical solution of the geometric information retrieval using advanced ML techniques will be mainly described.

FRAMEWORK OF AUTOMATIC 3D OBJECT-BASED INFORMATION RETRIEVAL

Geometric information retrieval of 3D object. The geometric information retrieval is powered by the integrated ML network (see **Figure 2**). The lighting fixtures are listed as the examples shown in the figure.

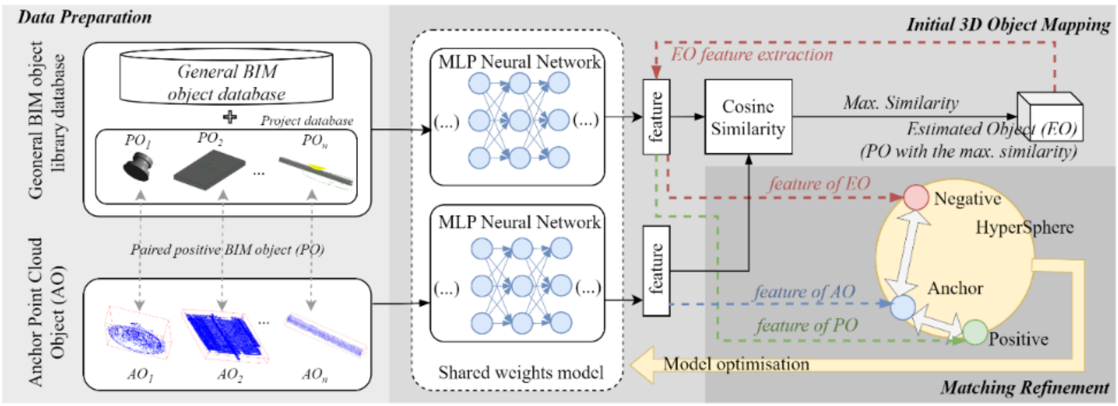

Figure 2 Technical pipeline of geometric information retrieval

- Data preparation: Two sets of data should be prepared, which are the Anchor Object point cloud model (AO) and the BIM object library. AO ($AO_1, AO_2, \ldots, AO_n$) in the **Figure 2** is the target of the retrieval process, which is a specific part of the point cloud model in a building asset that has been segmented and labelled. The BIM object library consists of two parts, which are the general BIM object library and project database. The general library is used for extracting features from specific categories of building elements and its 3D objects need to be converted into point cloud format. The project 3D object library refers to the restricted dataset which should be provided by property stakeholders, contains the positive selection of BIM objects (POs) matching with the AOs. It's crucial for this library to label each pair of PO (PO_x) and AO (AO_x) clearly, which is necessary for the supervised learning process in the neural network.
- Initial 3D object matching: This step includes two parts: feature extraction using Multilayer Perceptron (MLP) supported neural network and subsequent similarity calculation via Cosine Similarity (CS). MLP is a point-based method especially effective for dealing with non-uniform point density which are widely used in PCD processing work (Rauch & Braml, 2023). In the MLP neural network, the input layer receives the point cluster of AOs. The network has multiple hidden layers, where neurons apply activation functions to the inputs, facilitated by a system of weighted connections. The feature vectors will be extracted through the iterative feedforward and backpropagation process (Qi et al., 2017). After extracting the global signature of the point features from both the AOs and the objects in the BIM object library, the framework employs CS algorithm to identify the EO that bears the highest similarity to the AO. It is mainly used for the point-based similarity calculation (Collins et al., 2023; Huang & You, 2012). In the below equation 1), A and X represents the feature vector extracted from BIM object library and AO respectively. The framework proposes calculating the output features of

both datasets (the AO and the BIM objects) rather than directly comparing raw point cloud data, which is more effective due to the feature vectors are structured.

$$Cosine\ Similarity\ (A,B) = \frac{A \cdot X}{\|A\|\|X\|} = \frac{\sum_{i=1}^{n} A_i X_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \cdot \sqrt{\sum_{i=1}^{n} X_i^2}} \tag{1)}$$

- Matching refinement: The matching process will be further optimized based on the Triplet Loss (TL) method, which is a technique initially developed for classifying highly similar objects, such as in face recognition (Schroff et al., 2015). As shown in the below equation 2), the process involves: the anchor *A*, which is AO; the positive sample *P*, the matched object PO that corresponds to the AO; and the negative sample *N*, the EO identified in the previous step. The Loss Function *L* measures the distances between these samples with *d(A,N)* presenting the distance between the anchor and positive sample, and *d(A,N)* the distance between the anchor and negative sample. The 'margin' is a hyperparameter setting the minimum distance between dissimilar pairs. The optimisation of the feature extraction neural network is achieved through iterative processing using the gradient descent method on the *L* until the accuracy achieves a specific threshold for precise object matching.

$$L\ (A,P,N) = \max(d(A,P) - d(A,N) + margin, 0) \tag{2)}$$

Attribute information retrieval and knowledge extraction. Once the matched BIM object is identified, its associated attribute information can be retrieved. The attribute data represents the real-world attribute of the specific building 'secondary' objects. Take the lighting fixture as an example, the attribute can cover the information about material, power, light source, light colour, installation method etc. By gathering geometric and attribute data, the knowledge framework can be user-centred designed, which is based on the integration of industrial knowledge graphs. Consequently, the practical value of DTs can be enhanced in the real-world scenarios.

DISCUSSION AND CONCLUSION

This paper introduces an innovative framework to match 3D BIM objects for the target point cloud objects and it faces certain limitations that might need to be addressed. The primary limitation is the framework dependence on a pre-existing project library of 3D objects for both training and retrieval proposes. It operates under the assumption that the property stakeholders will supply the necessary information of the building assets. To tackle this limitation, two scenarios are proposed: The first scenario is the stakeholders are possessing the complete 3D BIM object library of their assets, necessitating the inclusion of both general and property-specific 3D BIM object databases in the training dataset. The second scenario caters to the situations where stakeholders have only attribute and dimension information without geometric information. Under this circumstance, the solution might be to develop an information query framework to locate the object in the general BIM object library with high-similarity geometric information, subsequently aligning it with the real-world asset's attribute information. This solution is proposed since the level of details of the object geometric information is less important than the attribute information and the current general object libraries typically cover a wide range of product geometric information and various design styles of common building components.

This paper proposes an integrated solution for extracting the 3D object-based information from scanned point cloud data aiming to address the research question. The future research will concentrate on four main areas: 1. testing and verifying the effectiveness of the neural network in retrieving information based on the case studies; 2. training the BIM object database for the neural network; 3. Adjusting the matched BIM object parametric and positioning in the DTs and 4. creating a linked data structure that organises both geometric and attribute information.

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