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A Scan-To-Bim Approach For Renovating Existing Building Rooms Using Surface Reconstruction and Deep Learning

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Abstract: Since global energy consumption is a critical issue and the building sector plays a significant role in high energy demand, renovating existing buildings is crucial. Building Information modeling (BIM) represents a building or structure's physical and functional characteristics with detailed information. It allows all the architecture, engineering, and construction (AEC) industry stakeholders to collaborate. As-built BIM models reflect the modifications of existing conditions of buildings, and fully automated generation of as-built BIM models remains a major challenge. The Scan-to-BIM process is widely used for the renovation and documentation of existing buildings. This process includes capturing the physical conditions of a building or structure using 3D laser scanning technology and converting it into a BIM model. Originally, 3D laser scanners had a very high cost, however, free 3D scanning applications that use Light Detection and Ranging (LiDAR) technology can be easily compatible with mobile phones or tablets nowadays. This paper proposes to contribute to renovating existing buildings by developing a new approach to scan-to-BIM, combining surface reconstruction from point cloud data and object detection with deep learning. A 3D free scanning application generated the point cloud data of the interior room of the building, and the surface model was reconstructed. Moreover, the location of the air terminals on the ceiling was investigated by developing the object detection model with deep learning and installing the air terminals on the surface-reconstructed model. The finalised surface model with the air terminals was exported to Industry Foundation Classes (IFC) format. The reconstructed IFC model developed in this research can be used for Computational Fluid Dynamics (CFD) analysis with appropriate property sets.

Keywords: Building Information Modelling, Surface Reconstruction, Object Detection, Deep Learning, Air Terminals, Indoor Environment Simulation

1. INTRODUCTION

Building energy consumption accounts for about 40% of global energy consumption, and the energy-saving retrofit of existing buildings provides a significant opportunity to reduce global energy consumption (Huang et al., 2022). A BIM model is a digital representation of facilities that records all information relevant to a building's life cycle from construction to demolition (Patraean et al., 2015). Building owners, facilities management groups, and governments are leading efforts to use BIM for new construction, renovation, or refurbishment of various facilities (Jung et al., 2018). In addition, it is important to note that the BIM created in the design stage of a facility is called as-designed BIM, and the BIM that reflects a facility in its as-built condition is called as-built BIM (Bosche et al., 2015).

As-built BIM are the key aspects in the renovation, maintenance, or further facility management as they support documenting the existing buildings by modifying the existing conditions. However, the traditional generating process flow of as-built models has several challenges, such as the necessity for a professional background for field surveys and measurements, taking time, and the low accuracy of the manual collection of data and remodelling (Varajic, 2020). Various technologies, such as photogrammetry and laser scanning, can generate point cloud data as the digital representation of the object or the scene. Therefore, combining modern technologies, such as laser scanning and LiDAR with BIM, can be a powerful tool for optimising the process, providing accurate data in less time (Qiu et al., 2021). Many efforts have been made to automatically develop BIM with these immediate survey datasets, such as a 3D point cloud or 3D mesh model with specific algorithms (Tang et al., 2022). However, the automated generation of the BIM model of indoor environments is challenged by the inherent noise and incompleteness of the data and requires further investigation (Tran et al., 2020).

Furthermore, object detection is a fundamental visual recognition problem in computer vision. It recognizes object categories and predicts each object's location by a bounding box (Wu et al., 2020). Deep learning (DL) has become the most widely used computational approach in the field of Machine Learning (ML) with its ability to achieve outstanding results on several complex cognitive tasks. One of the benefits of DL is the ability to learn massive amounts of data (Alzubaidi et al., 2021). Object detection with deep learning combines computer vision and neural networks to detect and localise images or videos automatically.

Based on these backgrounds, it is known that combining deep learning technology and Scan-to-BIM for indoor building rooms remains underexplored. Therefore, the research attempts to directly reconstruct the surface model from the point cloud and get the locations of the air terminals by object detection with deep learning. The main purpose of this research is to develop a new system of reconstructing the interior room of the building, including the air terminals, and use it for CFD analysis for further energy renovation processes.

2. RELATED WORKS

Indoor environment simulation of existing buildings is a key tool for improving comfort, air quality, and energy efficiency. BIM models can enhance simulations' accuracy, efficiency, and reliability, contributing to better-informed decisions not only for buildings but also for heating, ventilation, and air conditioning (HVAC) systems. Matsuba et al. (2023) developed a new IFC data model for BIM, sensors, and indoor environment simulation. However, their research exists an original 3D model of the building of interest. This study will reconstruct the BIM model of the existing building by directly scanning the existing building room.

Many researchers have developed various approaches to reconstructing indoor spaces from point clouds. Varghese et al. (2016) investigated the building boundary tracing and regularization from the LiDAR point cloud. Jung et al. (2018) developed a 3D volumetric reconstruction of multiple-room building interiors for as-built BIM. Xie et al.. (2017) reconstructed indoor buildings from mobile laser scanning data. However, the boundary generation method used in their studies started with point cloud preprocessing, such as noise reduction or clustering. Their boundary extraction is based on floor segmentation. The boundary generation in our study will overcome noise removal of the point cloud model by directly plane segmentation to the raw point cloud data and detecting the boundary points. The ceiling will be chosen for the plane segmentation so that difficulties in getting point cloud data of the exact floor shape due to the many furniture on the floor can be avoided. Moreover, their boundary regularisation used contour regularisation, which can lead to over-smoothing and irregular shapes. Our boundary regularization method will focus on each corner point and boundary line.

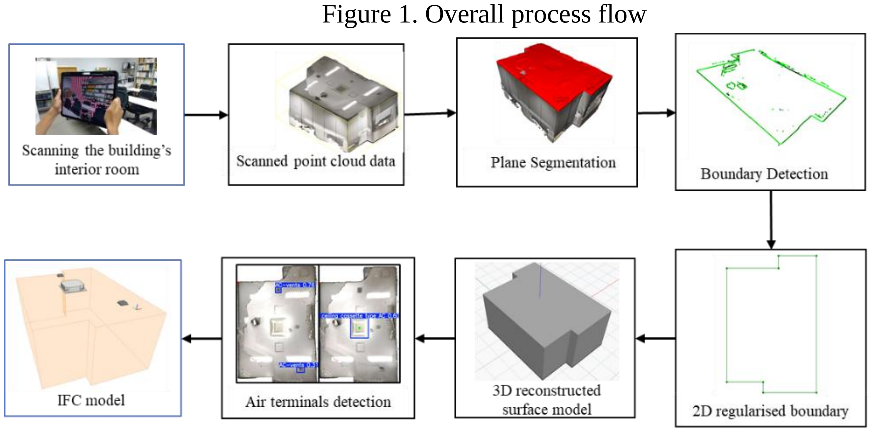
Ishikawa et al. (2021) directly and unevenly spaced Cartesian grids from laser-scanned point clouds without creating any 3D model. Their method needs ten scanned point clouds to register to generate the grid and has to manually assign the boundary condition for the placement of the air inlet and outlet. This study will create object detection datasets for air terminals to automatically figure out the locations of the air terminals of the existing building rooms.

3. DEVELOPMENT OF THE PROPOSED METHOD

3.1 Overview of the Method

The proposed method focuses on the 3D reconstruction of the interior room of the building for CFD analysis with three main steps: surface reconstruction, air terminal detection, and IFC modelling. Firstly, the point cloud model of the interior room is scanned using Scaniverse, a free application that uses LiDAR technology. The room's boundary points were extracted using plane segmentation and boundary detection algorithms. The concave hull algorithm changed the detected point cloud boundary to the line segments, and they were regularised. The regularised boundary was regarded as the floor boundary line, and floor-to-ceiling height was estimated by the histogram approach. The surface model was reconstructed based on the regularised floor boundary and estimated floor-to-ceiling height. As for the object detection part, the air conditioning and air-conditioning vents datasets were prepared and trained using the deep learning model. The finalised object detection model identifies the locations of the air conditioner and air conditioning vents on the ceiling using x and y coordinates relative to the leftmost top corner point. Based on these coordinates, air terminals were installed on the reconstructed surface model, and the finalised model was exported to IFC format. IFC is an open and standardised file format for sharing and exchanging BIM models across different software platforms developed by buildingSMART. The overall process flow is shown in Figure 1.

Figure 1. Overall process flow



Our research is supposed to generate the IFC model of the interior room of the building from the point cloud by the combination of surface reconstruction and object detection with deep learning. The plane detection and extraction on the ceiling allow the avoidance of manual processing of the noisy point cloud data due to the interior furniture. A user-friendly free 3D scanning application was used to get the point cloud data. The image of the point cloud model does not have enough resolution if compared with the normal images, and custom datasets were created for that. The final IFC model, including the air terminals, can be used for CFD analysis in future work.

3.2 Generation of the Surface Model from Point Cloud

Figure 2 shows the detailed process of generating a surface model from the raw point cloud. The red colour shows our original tasks, and the blue colour shows the existing tasks from the previous research.

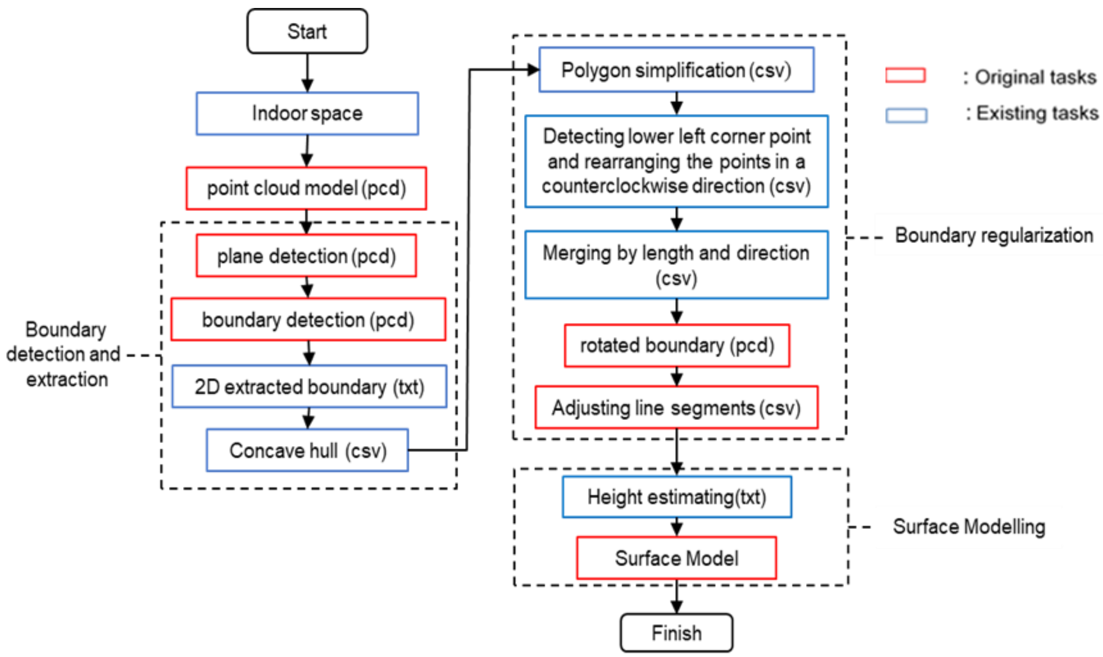
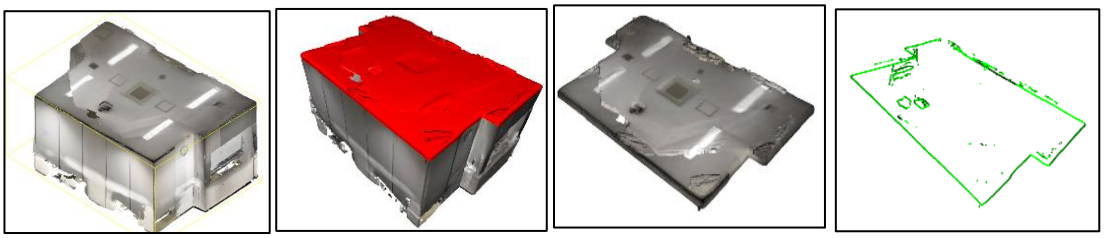


Figure 2. Process flow of wall-surface boundary generation

3.2.1 Boundary Detection and Extraction

The interior room of the building was scanned by Scaniverse 2.0.0 (Niantic, 2024) on iPad and exported into point cloud format, as shown in Figure 3 (a). The largest planar segment, the ceiling, as shown in Figure 3 (b), is identified using the Random Sample Consensus (RANSAC) algorithm (Fischler & Bolles, 1981) implemented in the Open3D library. In this step, the ceiling was chosen to be segmented (Figure 3 (c)) instead of the floor as the exact boundary shape of the floor is difficult to capture due to a lot of noises caused by furniture on the floor. The boundary points of the segmented ceiling were detected (Figure 3 (d)) by using the boundary detection algorithm (Mineo et al., 2019) of the Open3D library, which finds the boundary points among an unordered point cloud by analyzing the angle among the normal of a point and its neighbors.



(a) Scanned point cloud (b) Plane detection (c) Segmented ceiling (d) Detected ceiling boundary

Figure 3. Ceiling boundary detection and extraction

3.2.2 Boundary Regularization

The detected 3D boundary points were changed to 2D boundary points, as shown in Figure 4 (a), and connected with line segments by a 2D concave hull algorithm, as shown in Figure 4 (b). The concave hull was simplified as shown in Figure 4 (c) using the Douglas-Peucker Algorithm (Douglas & Peucker, 1973), which can reduce the number of points in a polyline approximation of a curve while preserving its essential shape. However, the simplified boundary still has curves on the main corners of the boundary. As a result, the boundary lines were merged based on their lengths and directional differences. Line segments that are shorter than a length threshold and have directional differences within a threshold are combined. One important thing to note before going to this step is that the sequence of the points directly extracted from the point clouds is messy, and the right length and directional differences of the adjacent line segments cannot be determined. To address this, the lower left point was detected, and all the points were arranged in an anticlockwise direction. The boundary merged by length and direction difference can be seen as shown in Figure 4 (d). As for the automatic rotation of the boundary line, the angle of deviation of the first line segment was calculated by trigonometric function. The rotation matrix was written based on the negative of the angle of deviation and applied to all the start and end points. The new rotated boundary is shown in blue as shown in Figure 4 (e). For the final regularisation of the boundary, the direction for adjusting the line segment was determined by comparing the absolute difference in x- and y-coordinates. For example, if the absolute difference in x-coordinates is smaller than in y-coordinates, the segment is more horizontally aligned and needs to be adjusted vertically. Following this, a vertical line was drawn from the start point's x-coordinate to the end point's y-coordinate by keeping the x-coordinate constant for a vertical adjustment, and a horizontal line was drawn from the start point's y-coordinate to the end point's x-coordinate by keeping the y-coordinate constant. The final regularised boundary can be seen as shown in Figure 4 (f).

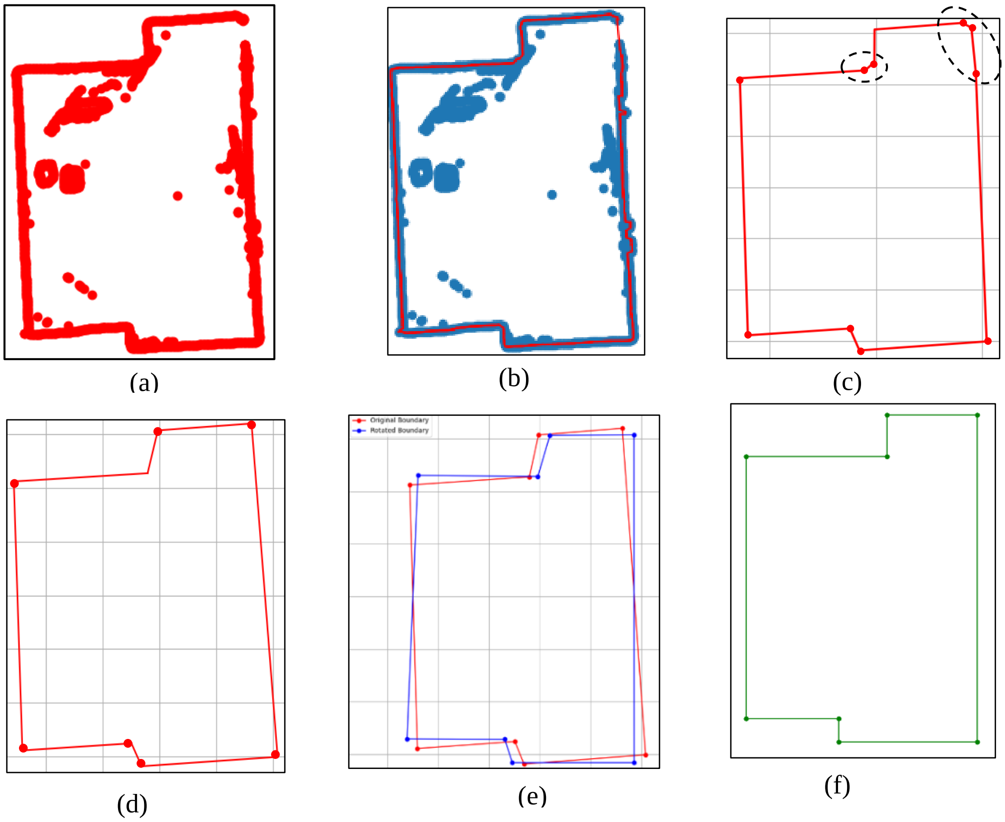


Figure 4. Boundary regularisation

3.2.3 Surface Modelling

Before proceeding to the surface modelling stage, the floor-to-ceiling height estimation was developed first. Many researchers have demonstrated the effectiveness of estimating floor-to-ceiling height using histograms (Turner et al., 2014), and we used this method for the estimation of the height of our proposed model. The z-coordinates of the point cloud model were extracted, and the mean z-values were computed. The low mean z-values were defined as the floor and the high mean z-values as the ceiling. The height difference between the two peaks shows the floor-to-ceiling height. The developed histogram is shown in Figure 5.

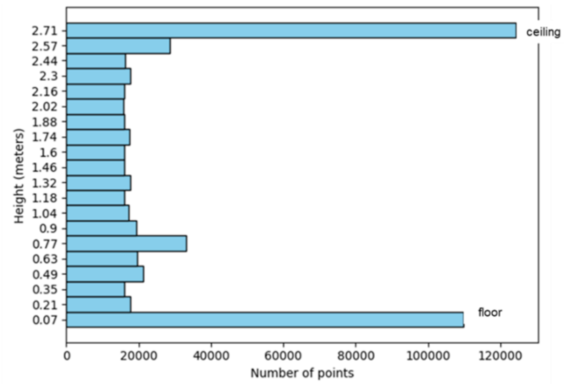
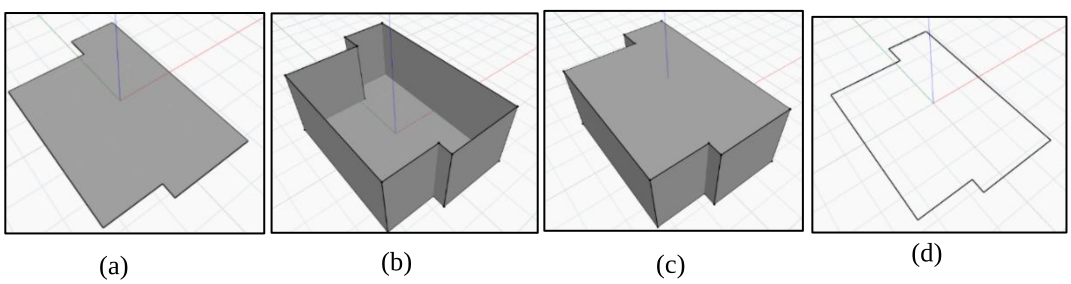


Figure 5. Histogram representing the number of scan points and their z-values

Afterward, the regularised boundary in the last stage was imported to the Revit Dynamo by Python Script. The imported line segments, as shown in Figure 6 (a), were joined as polycurves, and the floor surface was created as shown in Figure 6 (b). The wall surfaces were created by extruding the boundary line segments with the z-direction value of the estimated height by the histogram, as shown in Figure 6 (c). The ceiling surface was created by translating geometry from the floor with the z-translation. The reconstructed surface model of the room is shown in Figure 6 (d).

Figure 6. Surface modelling in Revit Dynamo



3.3 Detection of Air Terminals

3.3.1 Dataset Details and Training Conditions

This research developed two object detection datasets for detecting air conditioners (AC) and air conditioning vents (AC vents) with 218 and 281 images, respectively. The datasets' details are shown in Table 1. The collected images were manually annotated with Roboflow (Dwyer et al., 2024), an end-to-end platform for building, training, and deploying computer vision models. The target image for detection is the image of the point cloud ceiling, and AC vents have strikes that are difficult to capture well in the point cloud. To deal with this, augmentation was added while creating the AC vents dataset.

You Only Look Once Version 5 (YOLOv5) (Jocher et al., 2020) is the state-of-the-art object detection model designed for real-time detection of objects within images and videos. The datasets created were trained with YOLOv5, and the training results for each dataset are shown in Table 2. The development environment is shown in Table 3.

Table 1. Datasets details

	AC dataset	AC vents dataset
Number of images	218 (trained: 153, valid: 33, test: 17)	677 (trained: 594, valid: 54, test: 29)
Collection method	Canon Powershot SX710 HS, downloaded from pj Dataset	Canon Powershot SX710 HS
Image size	640 x 640 px	640 x 640 px
Annotation Method	manually	manually
Classes	2 (4-way ceiling cassette-type AC, wall-mounted type AC)	1 (AC vent)
Augmentation	N.A.	grayscale 30%, blur 25px, noise 5%

Table 2. Training results

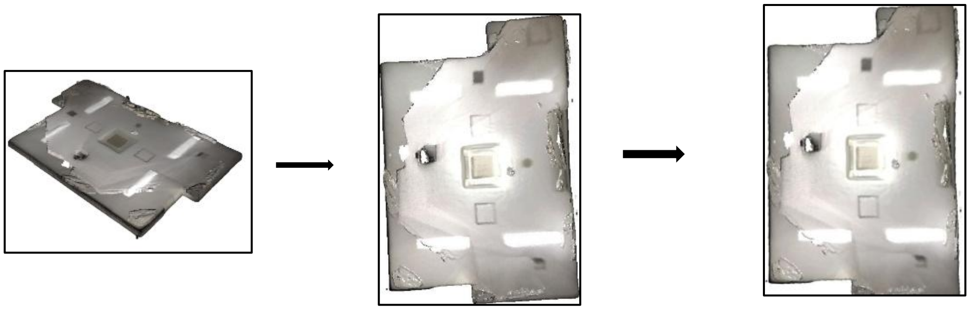
	AC dataset	AC vent dataset
Precision (P)	1	0.986
Recall (R)	0.972	1
mAP_{50}	0.994	0.993
$mAP_{50\text{-}95}$	0.875	0.851

Table 3. Development environment (desktop PC)

OS	Windows 11 Education 23H2
CPU	12^{th} Gen Intel(R) Core (TM) i7-12700
RAM	32.0 GB
GPU	NVIDIA GeForce RTX 3060 Ti

3.3.2 Detection Results

For the testing of the prepared object detection model, preprocessing of the input image is necessary. Initially, the point cloud of the segmented ceiling as shown in Figure 7 (a) was converted to an RGB image as shown in Figure 7 (b) with Open3D and Numpy libraries. To ensure that the object was properly centred in the image, the blank space around the main object was trimmed using a custom function with Python Imaging Library (PIL). Subsequently, the main object inside the image was rotated using the same method in the boundary regularisation stage. The edges of the objects in the image were detected by Canny edge detection (Canny, 1987) and vertical lines were identified by Hough line transform (Hough, 1962), focusing on those with angles between 80 and 100 degrees. Then, the inclination angle of the first detected vertical line was calculated and the object in the image was rotated as shown in Figure 7 (c). The detection results with the prepared object detection model on different images can be seen in Figure 8.



(a) 3D point cloud of the segmented ceiling

(b) 2D RGB image of the point cloud ceiling

(c) Rotated object inside the image

Figure 7. Preparation of image for object detection

Input	Output	
	AC dataset	AC vents dataset
		
		
		

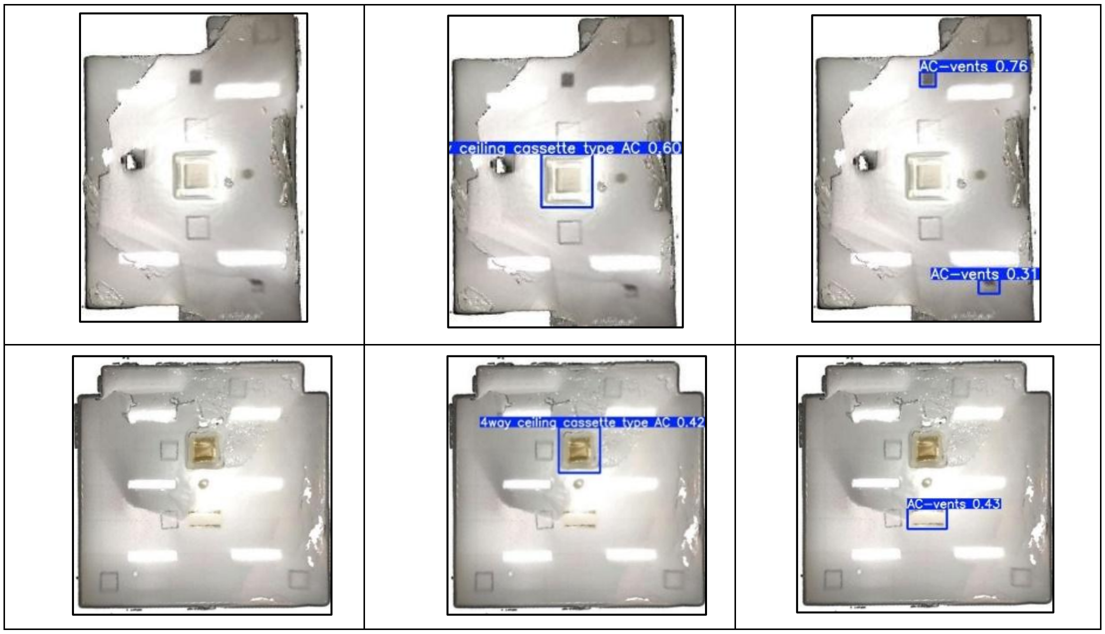


Figure 8. Detection results

3.4 Modelling of AC Terminals and Generation of IFC Model

Firstly, the centres of the bounding boxes of the detected objects were computed. Then, the left-top corner point was detected by the Shi-Tomasi Corner Detection Method (Shi & Tomasi, 1994) with the OpenCV library. The distances between that corner point and the bounding box centres were evaluated. Finally, the pixel coordinates were converted to real-world coordinates by multiplying by the pixel size. The centre points of the AC and AC vents were added to the ceiling of the surface model, considering the left-top corner point as the reference via the Point.ByCoordinates Dynamo node, as shown in Figure 9.

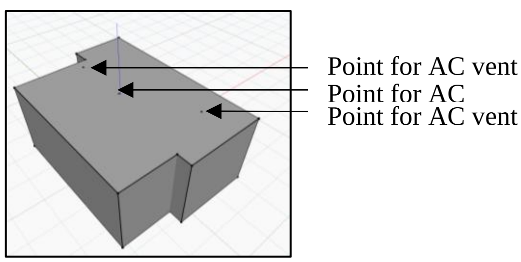
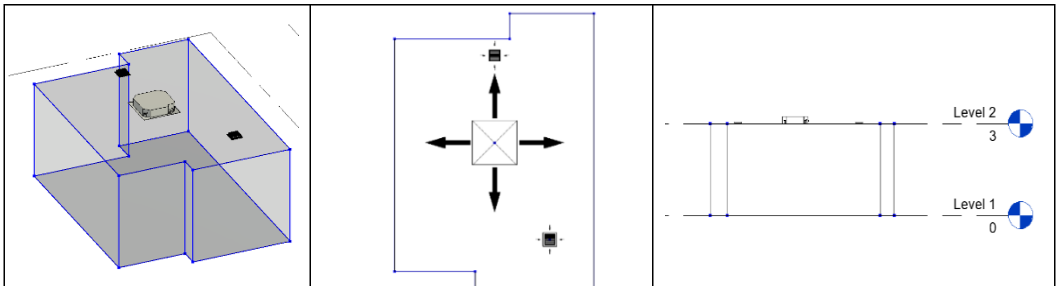


Figure 9. Locating the points of AC and AC vents in Dynamo Revit

The AC and AC vents were added to the surface model by FamilyInstance.The ByPoint Dynamo node requires the family type and point as inputs. The AC family, downloaded from the BimObject website and loaded into Revit, was connected to the family input. The AC location points calculated from the last stage were connected to the point input node. As a result, the AC and AC vents were automatically added and aligned on the ceiling of the surface model, as shown in Figure 10.



(a) 3D view (b) Floor plan (level2) (c) Elevation (west)

Figure 10. Different views in Revit

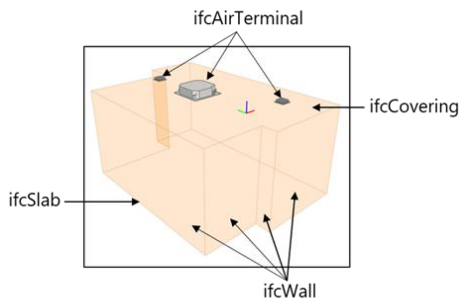


Figure 11. IFC model viewed on BIM Vision

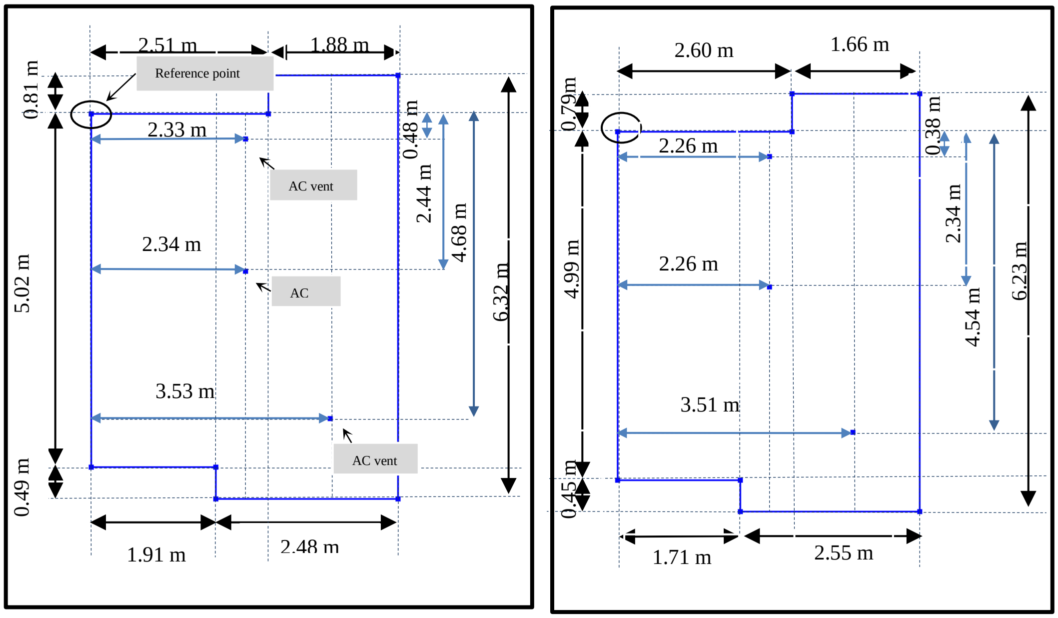
The reconstructed surface model was exported to the IFC4 schema, as shown in Figure 11, using Autodesk Revit. IFC4 offers more comprehensive property sets for HVAC elements like air terminals by supporting detailed attributes for flow rates, pressure losses, and performance data, which are vital for CFD analysis.

4. ACCURACY ASSESSMENT

The Intersection over Union (IoU) method was used to check the accuracy of the reconstructed surface model. IoU is a powerful metric for comparing two shapes based on their overlap, and the IoU of the developed model in this research is calculated as the area of the intersection divided by the area of the union of the concave hull from the extracted boundary and the final regularised boundary. Details can be seen in Table 4. The comparison between the ground truth model and the reconstructed model is shown in Figure 12.

Table 4. IoU Result

	Area (m^2)	Area of Intersection (m^2)	Area of Union (m^2)	IoU
Concave hull from the extracted boundary	24.58	23.28	25.01	0.931
Regularised boundary	23.71			



(a) Ground truth model (b) Reconstructed model

Figure 12. Comparison between the ground model and reconstructed model

5. DISCUSSION

This research developed a new method of generating an IFC model of the existing building rooms from point cloud data. The scanning device used in this research can be compatible with mobile phones or tablets and is easily accessible to users without a professional background. Unlike most previous studies, which emphasise extracting the boundary from the floor, our method addresses the challenges of noise removal and getting the exact boundary shape directly from the point cloud. The boundary detection in our study is achieved by segmenting the ceiling through plane detection, and there is no need to worry about not getting the exact boundary shape due to a lot of furniture on the floor or the tall bookshelves against the walls. This research developed two custom datasets aimed at detecting the air terminals inside the images of the point clouds, which have lower resolutions compared to normal images.

However, certain stages in boundary line generation from the detected point cloud boundary in this research require the user to manually set the parameter thresholds. This can lead to time consumption and data instability. Developing a program that selects the appropriate parameter thresholds for different input data would enhance productivity. Additionally, this research's boundary regularization method focuses on points and straight-line segments, limiting its applicability to interior rooms with curved boundaries. The openings, such as doors and windows, were not considered in this research. Detecting the air terminals, particularly the AC vents, faced significant challenges due to the lines on them, which were difficult to identify because of their low visibility in the point cloud images. As a solution, two datasets were developed separately for AC and AC vents with different augmentations. Future research should explore more efficient methods for linking the point cloud data to the reconstructed model directly or how to generate a unified dataset able to detect all air terminals in point cloud images.

6. CONCLUSIONS

In conclusion, this study demonstrates a new approach to Scan-to-BIM by combining surface reconstruction and object detection with deep learning. The free application on tablet generated the point cloud data used for this research and can be easily accessible by everyone who lacks specialised knowledge and experience. The boundary detection and regularisation methods introduced in this research enable the rapid and accurate generation of exact boundary shapes, closely matching the real room's boundary shape. All the steps, from plane detection to boundary regularization, were completed by a Python script without using any manual or paid software. The surface reconstruction from the boundary line segments and the installation of the air terminals using the location obtained from object detection were accomplished with the Revit Dynamo. As for the air terminal detection, deep learning-based object detection was utilised, and custom datasets specifically focused on the point cloud image were developed.

Future work will expand the object detection part by considering the openings, such as doors and windows, as well as material types. Additionally, the IFC model developed in this research will be enhanced by integrating the custom property sets prepared for CFD analysis.

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