Detection of building fixtures in 3D point cloud data

H Mansor¹, S A Abdul Shukor¹, R Wong²

¹ Faculty of Electrical Engineering Technology, Universiti Malaysia Perlis, 02600 Arau, Perlis, Malaysia.
² Geodelta Systems Sdn. Bhd., 47400 Petaling Jaya, Selangor, Malaysia.

humairah@unimap.edu.my

Abstract. Building architectural and civil engineering are constantly changing, causes the increases of building spaces as well as renovation works which includes structures such as walls, ceilings and floors, and building fixtures. Building fixtures are objects which is secured to the building, such as lighting fixtures, plug and socket, ceiling fan and so on. It is considered as one of the complex structures in building as the size of the fixtures are small and sometimes are hardly seen immediately. When a certain building changes, the building information need to be updated along with the changes of the building. The process to update the changes has contributed towards complex and huge data to be processed which usually involves tedious and complicated work. Therefore, to recognize the fixtures in building environment before renovation, an object recognition method is applied. This investigation focused on the recognition of lighting fixtures in the environments. By using MATLAB, an algorithm is developed to detect the point cloud data that belongs to the lighting fixtures. The investigation shows that the lighting fixtures can be identified by using Region of Interest (ROI) method within an environment. From the results, the accuracy of the dimensions of the lighting fixtures detected in point cloud data compared to the real one in the environment is 75% and 72% match, which is good but still need an improvement to be closely match with the real dimensions. The finding is hoped to simplify the tasks of determining the fixtures in the building before any changes is done.

1. Introduction

Object recognition from point cloud data has been numerously studied nowadays, as it is one of the basic tasks in computer vision. This includes detection of human, vehicles and important objects in respective area. Mostly, the work covers 2D image data, but this trend has changed recently due to the advancement in processing the 3D point cloud data. The spatial geometric structure of 3D point cloud data is certainly clearer compared to 2D data. However, the 3D point cloud data textural information is not as clear as 2D. Moreover, it can be affected by noise, clutter and occlusion and the data also are very large in size that it needs to be processed into several parts. Object recognition and classification usually comes with a point cloud segmentation, which is a process of grouping the point based on the similar low-level attributes. This process allows the analysis to classify or recognize an object to be framed to a small subset of data, which can significantly reduce the complexity and size of the data. The data size can be further reduced by modelling these objects for advanced analyses, so that the simplified models is produced rather than bulkier point clouds. Once the objects are extracted and classified, the unwanted noise and object can be removed easily [1]. Once the process of segmentation is done, object recognition and classification were proceeded. Object recognition helps to recognize types of objects segmented in point cloud data and the classification process allocate a class to each point, segment, or object to
represent certain type of object. In this project, the object recognition and classification will be focused on indoor building environment, specifically building fixtures in the building.

Building fixtures are one of the most important elements in a building. The building fixtures are an asset that is installed or fixed in or to a building to become part of that building [2]. Usually, the building fixtures instalment are based on the building owner’s requirements. The location of building fixtures is particularly important since the drawings and specifications, contracts and health and safety manuals will be referred to them [3]. Therefore, it is important to acknowledge where the building fixtures are mounted in the building. Due to this importance, this paper will discuss on the building fixture detection from 3D point cloud data, which focused on lighting fixture in the building. Figure 1 shows several types of lighting fixtures commonly used in a building.

![Figure 1. Several types of lighting fixtures available in a building [4]](image)

2. Previous work
Detection of various shapes is complicated since it involved a huge amount of data in complex environment. In order to detect the shapes in point cloud data, several methods have been utilised by previous researchers. These are object instances recognition, object classes recognition, recognition using context and lastly using prior knowledge [1]. Since this paper focuses on detection of object in a building (specifically fixtures), we will go through previous research involved with object detection from the point cloud data within building environment.

Object instances recognition is a process of object detection from a known class, such as people, cars, or faces in an image [5]. In the context of building environment, one of the previous researches that has been widely investigated is windows recognition in point cloud data. Since the laser scanner, the device that is usually used to collect point cloud data, cannot capture windows accurately because of their transparency, several researchers had come up with some solutions. Shi Pu et al. [6] conducted a research to extract windows from building facades. The research used hole-based extraction method, where any holes detected at wall feature segment are considered as windows. Meanwhile, Bohm et.al.[7] in their research used density-based edge detection to identify the vertical and horizontal lines of building facades. The resulting rectangles are then classified to window or non-window.

Object classes recognition is a process of class membership identification (eg., a car, a dog, a person) of certain object contained in an image [5]. Examples of object classes recognition involved in clutter and occlusion environment. This is usually involving in-used buildings and very challenging since there will be many noises that needs to be eliminated in order to detect the targeted object. Besides that,
Antonio Adan et al. [8] proposed a learning-based method for detecting and modelling openings and distinguishing them from similarly shaped occluded regions and propose a method for evaluating reconstruction accuracy. Victor Sanchez et al. [9] presented an automatic system for planar 3D modelling of building interiors from point cloud data. The interiors include ceilings, floors, walls and staircases. Model-fitting and RANSAC were proposed for large-scale structures detection, such as ceiling and floors, to small scale architectural structures, such as staircases.

Approaches based on context use relations between component to learn the unique features of different types of surfaces and the contextual relationships between them. The knowledge is used to label patches as walls, ceilings, or floors [1]. Another research conducted by Shi Pu et al. [10] introduced knowledge-based features to extract walls, roofs and windows. A polyhedron building model is combined from extracted features to form a building.

Another category of object detection is using prior knowledge. Prior language is a comparison between ‘as-built’ and ‘as-designed’ BIM in detecting any differences between these two. Yue et.al. [11] has conducted a project to detect defects on construction sites by comparing the as-built BIM to as-designed BIM. From this method, the accuracy between the point cloud data and the actual object can be compared.

In summary, it can be concluded that although there has been many research conducted on object recognition and classification of point cloud data for building, there are still many gaps to improvised. One of the reasons is to expand the research on more complex details, such as columns, structural steels and cove ceilings [1]. Besides that, exploring the detection techniques of fine details such as decorative mouldings and lighting fixtures would also be promising. The research of fine details detection is useful especially for a highly detailed building facades such as historical buildings. Last but not least, the improvement also can be made in handling the openings, such as windows, doors and closet, and see-through walls objects as these also have their own challenges in recognition process.

3. Methodology
This section elaborates the flow of the work that has been done to detect lighting fixture along the corridor of the building. The point cloud data collected at the scene are using lidar scanner model Leica RTC360D. the laptop used to process the point cloud data is Asus brand with AMD Ryzen processor and 500GB hard disk capacity. The scene chosen for this project is the Faculty of Electrical Engineering Technology, Universiti Malaysia Perlis, Malaysia. The chosen scene is along the corridor of the faculty at Meka 3 wing, which has lighting and piping fixtures at the ceiling. MATLAB R2020b student version is chosen as the software to process the point cloud data.

3.1. Segmentation process
Segmentation is a process of dividing the point cloud data into several regions. This process was done to simplify the point cloud data and facilitate the process of classification. The segmentation process uses the concept of RANdom SAmple Consensus (RANSAC) algorithm. Every plane in 3D point cloud data can be represented by equation (1) below:

\[ ax + by + cz + d = 0 \]  \hspace{1cm} (1)

where \( x, y, \) and \( z \) are the 3D point in the space, while \( a, b \) and \( c \) represent the normal vector and \( d \) is the distance of the plane from the origin. For the probability of success, the number of RANSAC iteration, \( N \) can be calculated using the equation (2) below:

\[ N = \frac{log(1-p)}{log(1-(1-e)^s)} \]  \hspace{1cm} (2)

where \( p \) is probability of success (0.90-0.99), \( e \) is probability that the point is outlier and \( s \) are number of points in a sample. For this experiment, \( s = 3 \) since it is the minimum point to forms a plane. From the original point cloud data, an algorithm is applied to segment the point cloud into several regions, which is ceiling, floor, left wall, right wall, front wall, and back wall. Firstly, the first plane (ground) of the
point cloud data is extracted. The data of the ground are all considered as the inliers data and the remain point cloud data is considered as the outliers. After the point cloud data belongs to ground is extracted, the next planes will be extracted from the remain point cloud, which is all the outliers from the extraction process before. After these six regions were segmented, the remain point cloud data will be taken out to detect which remains belongs to building fixture, which is in this scope, the lighting along the corridor.

3.2. Object Recognition Process

Once the segmentation process is done, object recognition process will take over. In order to detect the object, Region of Interest (ROI) node of the point cloud data is set. This step applied Region of Interest (ROI) which returns the points within ROI in the input point cloud using a Kd-tree based search algorithm. The specified region of point cloud was set by limiting the range for each axis (X\text{limit}, Y\text{limit}, Z\text{limit}) of properties in location. The points within the specified ROI are obtained using Kd-tree structure. From the Kd-tree structure, K-Nearest Neighbours (KNN) is used to find the point in the tree that is nearest to the input points. Figure 2 below shows the point cloud data of lighting fixtures in specified ROI.

![Figure 2. The point cloud data of lighting fixtures in specified ROI](image)

3.3. Object classification process

After the data is segmented and ROI is set, there are still some parts and noises left with the simplified point cloud. Therefore, the selected point cloud should be processed again until the lighting fixture can be seen clearly and easier to be detected. In order to perform the task, the unwanted parts are deleted and only the respected data is chosen by using data tip option in MATLAB figure. The final figure is stored as a point cloud object. After that, an algorithm based on KNN concept is applied to identify which object belongs to lighting fixtures.

4. Results and discussions

The results of the process can be seen in figure 3 to figure 6. Figure 3 shows the original point cloud taken from the laser scanner. The point cloud data is very dense; thus, segmentation process is performed to detect the lighting fixture. Figure 4 shows the remaining point cloud after the segmentation process is performed. From here, we can see interested fixture, i.e., the corridor lighting which mounted on the ceiling.
Figure 3. Original point cloud data taken from laser scanner.

Figure 4. The remaining point cloud data after segmentation process.

Figure 5 shows the deleted unwanted parts and figure 6 shows the final data that will be used to detect the lighting fixture using ROI.

Figure 5. Point cloud data with some of unwanted parts.

Figure 6. The final point cloud data that will be used to detect the lighting fixture.

From here, an algorithm to detect the lighting fixture in the point cloud data is applied, based on Region of Interest (ROI) concept, where the point cloud data that contained the dimension (width x length) of the lighting fixture within the region is detected and coloured to get the object features. The result is shown in figure 7.
To validate the results, the detected lighting fixture measurement is compared with the original data. Table 1 summarised the validation results. From here, we can see that the reference width and length of the lighting fixture is 30.48cm x 60.96cm while the measured size is 21.95cm x 45.72cm. The measurement of the actual lighting fixture is taken from the specification sheet and the measurement of the measured lighting fixture in point cloud data is taken from the difference of x-axis and y-axis as shown in figure 2 which represents the length and the width of the fixture. The accuracy percentage of the actual dimension to the measured dimension is calculated in table 1.

|       | Actual dimension | Measured dimension | % Accuracy (measured dimension/actual dimension x 100%) | % Difference (100% - % accuracy) |
|-------|------------------|--------------------|------------------------------------------------------|----------------------------------|
| Width | 30.48cm          | 21.95cm            | 72%                                                  | 28%                              |
| Length| 60.96cm          | 45.72cm            | 75%                                                  | 25%                              |

From table 1 above, the accuracy percentage of the lighting fixture is 72% and 75% for the width and length, which is above 50% for both dimensions. The difference percentage is 28% for width and 25% for length. As of the current progress, the algorithm is only tested on one environment, which is along the Meka 3 wing. For future improvement, we will test the algorithm in another environment and minimize the accuracy percentage closest to the BIM standard which is 0.32cm to 5cm difference [12].

5. Conclusion
In this paper, we present an object detection in 3D point cloud data using Region of Interest (ROI) for lighting fixtures in the building environment. The method involved segmentation, object recognition and classification to process the raw point cloud data into the simplest data. The result of the research shows that the lighting fixtures are successfully identified in the building environment. The accuracy percentage of the actual dimension to the measured dimension is 72% for the width and 75% for the length. For future work, an improvement can be done in the process of eliminating the unwanted noises of point cloud data, alternate part segmentations, and geometric part analysis for 3D object classification in clutter and occlusion [6], hence the work of this paper. The result also can be improved by using another method available, such as deep learning algorithm and expand the work on more complex objects without the need to simplify the point cloud data.
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