Point Cloud Data Segmentation Using RANSAC and Localization

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Abstract. In this paper, we present 3D point cloud data segmentation from a Terrestrial Laser Scanner (TLS) using RANSAC and localization approaches. Our work is using the real world data acquired from outdoor and indoor scene of Tawau Bell Tower (also known as the Belfry), one of the heritage building located in Sabah. We adapt the methods to segment ground and non-ground data for data reduction. Based on the non-ground information and geometrical constraint, the data managed to show the building structure. The aim is to use and handle a smaller set of data rather than using the entire point cloud data in processing the region of interest. This will also help to reduce processing time as point cloud data from a TLS is usually large in size. The ground plane was fitted with RANSAC algorithm restricted by distance to describe the geometrical of the plane. As a result, the point cloud data was reduced to the environment around Bell Tower and able to highlight the region of interest. Building segmentation is then retrieved from the reference centre location to form a bounding box and data were organized using kd-tree to denote the Bell Tower structure. The framework is tested for outdoor and indoor scan of the Bell Tower and able to segment the data appropriately.

1. Introduction

At present, documentation of heritage buildings are moving towards on the usage of laser scanner technology for cultural preservation [1]. Terrestrial Laser Scanner (TLS) is preferred because of its capability of acquiring accurate data in a short time [2][3]. TLS captures the object and the scene information in millions 3D point cloud that able to ensure the details of the building surface and its surrounding are collected. However, this will leads to a large file size to be managed. Hence, this has attracted the interest among researchers in processing and analysing the data.

Apart from that, the challenges in point cloud data processing could also be started as early as the data acquisition process. TLS acquires data at same platform and different terrain height can cause some difficulty to differentiate ground and non-ground elements [4]. The system too could not automatically capture targeted object only as it will collects data from any physical surfaces of the entire scene. By segmenting ground and non-ground, this will help to differentiate the data into regions and give topology
simplification to the data [5]. Thus, the data will be smaller in size and will be easier to be managed for further processing, plus at a reduced processing time. In this paper, we adapt data reduction approach to segment it into ground and non-ground. Random Sample Consensus (RANSAC) approach is used for segmenting ground plane. Geometrical constraint representing non-ground data consists of building and vegetative is used to describe the object of interest retrieved from the location of the reference centre that forms the bounding box. The point cloud was organized using kd-tree data structure. This method is applied in the real world scene for outdoor and indoor scan of Tawau Bell Tower.

2. Related work
Researchers use geometric adaptation as the approach in segmenting object of interest from terrain. RANSAC is one of the robust method used in geometrical fitting [6]. The method adapts mathematical concept based on model shape such as plane, cylinder or sphere. The algorithm randomly select model data points according to geometrical shape. In contrast, other methods like 3D Hough transform requires sensitive parameters such as discrete axis value and threshold for segmentation which difficult to determine because of its dependency on point cloud characteristic [7]. Furthermore, small value parameters are required by 3D Hough transform for good plane detection thus it needs more processing time and memory. Hence, RANSAC provide advantage in negligible processing time over large data size by randomly search that will reduce iterations [8].

Other researchers use hybrid model fitting method to improve the efficiency of RANSAC for segmentation. A study by B.Oehler et al. stated that by combining RANSAC and 3D Hough transform for planar segmentation will give good efficiency. They used Hough transform as a coarse solution and then make it finer with RANSAC to fit the plane. Although their method provide large possible plane surface, it is only limited for indoor scene [9]. Meanwhile, T. Czerniawski et al. extracted plane of building using extended RANSAC by concentrating in region of interest. Their approach able to select feature extraction for further classification process [10]. F. Poux et al. deal with image and point cloud data for their study. They used RANSAC to detect shape of tessera for cultural heritage preservation. The algorithm managed to extract details of tessera with best fit of bounding box [11]. From here, it can be seen that RANSAC is useful for data segmentation. Therefore, our study utilizes RANSAC approach for outdoor and indoor 3D point cloud data segmentation. As the data size will be reduced, working with small data will make it easier for segmenting object of interest from the scene.

3. Datasets
Point cloud data used in this research is from a heritage building environment. The data was acquired using a TLS and the data collection process is explained in details in this section.

3.1. Study area
Tawau Bell Tower or also known as the Belfry is located in Tawau and was constructed as the evidence of previous British government before Sabah became part of Malaysia. The historic building is almost 100 years old and it is the oldest monument that was safe during the Second World War. The Bell Tower was built by prison labourers to remember the resolution undersigned during First World War when Japan became cronies of England. This building was refurbished by Rotary Club of Tawau and passed to Jabatan Muzium Sabah on 2006 [12].

3.2. Point cloud data acquisition
The point cloud data representing the building is provided by Geodelta Systems Sdn. Bhd. acquired using Leica HDS6000 TLS. The TLS is capable to scan up to 500,000 points per second and this system is equipped with a NIKON D80, 10.2 Megapixel camera. They located the scanner into 10 stations respectively to obtain the whole Bell Tower building data. Figure 1(a) shows the location of the TLS from station one to station ten (St1-St10), while Figure 1(b) and 1(c) represent St1 and St10 point cloud data respectively. In this paper, we process the first station (St1) for evaluating the effect of different radius of obstacle and object of interest as well as sensor location to the segmentation approach.
Figure 1. Bell Tower data: (a) Location of scan station, (b) station one (St1) and (c) station ten (St10) point cloud data.

The raw point cloud data are available in .zfs, which is in binary file format consist of XYZ coordinate intensity and colour information. In order to process the data, it needs to be converted to a nonproprietary format like ASCII. Autodesk ReCap and CloudCompare software were used in this case to obtain the .ply file format and the conversion process can be seen in Figure 2. Then the data processing is done by using MATLAB R2018b and 64 Bits Windows 10 with Intel Core i5-4200U (1.60GHz) 12 GB RAM.

Figure 2. File format conversion (binary to ASCII).

4. Methodology
There are three stages involved in this point cloud data segmentation using RANSAC for ground plane fitting and localization for nearest neighbour in radius to find the object of interest. Firstly, the region of interest was selected to highlight the environment around object of focus. Secondly, segmentation of ground plane was used to show information for ground surface and non-ground objects in the scene. Lastly, the non-ground objects were segmented according to their locations.

As the normal directions of the plane are pointing in vertical direction, thus it can be calculated using equation 1:

\[ aX + bY + cZ + d = 0 \]  

where \( X \), \( Y \), and \( Z \) represents 3D point in the space, while \( a \), \( b \), and \( c \) are the normal vector for the respective axes and \( d \) is the normal vector passing through origin.

The distance from the point to the plane, \( D \) can be found using equation (2):

\[ D = \frac{aX+bY+cZ+d}{\sqrt{a^2+b^2+c^2}} \]  

The number of RANSAC iteration, \( N \) can be calculated using equation (3):

\[ N = \frac{\log(1-p)}{\log(1-(1-e)^{s})} \]
where $p$ is the probability of choosing a good sample, $e$ is the probability of choosing outliers with 99
do of desired confidence percentage and $s$ is the initial number of points to fit the model, where in this case, $s=3$.

Algorithm 1 shows the pseudo-code of the overall work, where the input data are 3D point cloud, $pc$, $d$, $v$, $s$, $r1$ and $r2$ respectively, and their description are discussed in Section 4.1 to 4.3.

Algorithm 1: Pseudo-code of building segmentation using RANSAC and localization approach

1. $pc=\{Xlimit; Ylimit; Zlimit\}$;
2. for maxDistance = $d$; reference vector = $v$;
3. fit plane outliers ($pc$, $d$, $v$);
4. then label inPlanePointIndices = greenIdx;
5. else select outliers = $pc$ without $ground$;
6. end for;
7. for sensor location = $s$; radius = $r1$;
8. find neighbours in radius, nearIndices ($s$, $r1$, $pc$ without $ground$);
9. then label nearPointIndices = RedIdx;
10. end for;
11. while radius = $r2 < r1$;
12. find neighbours in radius nearIndices = (pcWithoutGround; $s$, $r2$);
13. then buildingPointIndices = outliers (nearIndices);
14. select pcBuilding = (pcWithoutGround; nearIndices);
15. do bounding box for pcBuilding then label BlackIdx;
16. end; Return for sequence $pc$

4.1. Region of interest selection

This work started off with the selection of the region of interest from raw point cloud, $pc$ in order to emphasis on the main information to be delivered from the scene. This method is aimed to manage big data focused on region of interest rather than processing the data of the entire scene. The data from CloudCompare software (in .ply file) was loaded into array structure and it stored object in 3D point cloud properties as location (X, Y, Z), intensity value (I) and RGB colour. The displayed region of point cloud was set by limiting the range for each axis (Xlimit, Ylimit, Zlimit) using properties in location. We reduce the raw data of every scan stations to region of interest by 16m x 16m for x-axis and y-axis respectively, based on the region of Bell Tower location. No limitation set for the z-axis as the captured data are from panorama view and to allow free constraint for the horizontal scene that represents the whole building. Figure 3(a) and 3(b) show actual raw data and its region of interest for St1.

4.2. Segmentation of ground plane

The ground plane was then fitted using RANSAC algorithm. Therefore all inlier points are assumed as the ground plane. The points that did not belong to the inliers of ground plane are considered to be the outlier points which were then removed. The ground was segmented according to the outliers point set at maximum distance, $d$ by 20cm above the ground plane constrain from reference vector, $v$ at (0, 0, 1). Figure 3(c) shows the resulting data with the ground plane removed for St1.
Figure 3. (a) Raw data from St1, (b) region of interest, (c) region of interest without ground.

4.3. Segmentation of non-ground objects

From the scene shown in Figure 3(c), it can be seen that the Bell Tower are surrounded with obstacles due to overlapping from nearby tree. Therefore, a radius of obstacle, \( r_1 \) is created to note the boundary to the Bell Tower. The obstacle point was retrieved from the sensor location, \( s \) of reference point at centre of the Bell Tower. The radius of obstacle should be larger than radius object of interest \( (r_2 < r_1) \) in this approach. The nearest neighbour points are considered outliers at given radius within the non-ground points. We denote the obstacle with red colour.

The centre point of Bell Tower can be estimated from the location of 3D point cloud plot in Cartesian plane. This reference point of sensor location was used to track the Bell Tower. The algorithm finds the nearest neighbour point to the sensor location as the object of interest, thus smaller radius was set to encompass Bell Tower out of the obstacle radius. The point cloud data was arranged using kd-tree structure and bounding box to represent the Bell Tower.

5. Results and discussion

Point cloud data captured from outdoor scanning are more challenging compared to indoor scanning in terms of size data capture by TLS [13]. Some researchers also stated that outdoor scans required more attention as it involve interferences such as light reflection [14]. Evaluations on parameters of radius and sensor location are discussed in following section.

5.1. Effect of localization and parameter of radius

The localization of the object of interest with respect to the reference centre is subject to the data acquisition by the TLS at different platform. Changes in reference centre of sensor location and radius will produce oversegmentation and underssegmentation based on experiment using St1. Figure 4 shows the effect of changing sensor location and radius of obstacle and radius. The best segmentation using this approach can be seen in Figure 4(a). With respect to radius of Bell Tower, it can be seen that the black colour over segment the leaves from the tree that overlapping on the roof of the Bell Tower shown in Figure 4(b). Meanwhile, undersegmentation can be observed in Figure 4(c), as the parameter of the same reference centre and smaller parameter for radius. Here, the black colour is under segment the leaves. This scenario usually happen for case dealing with trees as an obstacles [15]. Therefore, reference centre of object detection and radius set for algorithm are in relationship with each other to determine the success of the segmentation. Overall, our approach has able to segment the ground data and the object of interest.
5th International Conference on Man Machine Systems  
IOP Conf. Series: Materials Science and Engineering 705 (2019) 012004  
doi:10.1088/1757-899X/705/1/012004

(a) Reference centre (-5.5,0), radius Bell tower = 8m, radius obstacle = 6m.
(b) Reference centre (-7.4,0), radius Bell tower = 8m, radius obstacle = 6m.
(c) Reference centre (-5.5,0), radius Bell tower = 7m, radius obstacle =5m.

Figure 4. Segmentation of St1 scan station (a) Well-segment, MSE = 0.402m, (b) oversegmentation, MSE = 0.482m and (c) undersegmentation, MSE = 0.501m.

5.2. Evaluation of segmentation approach
Researchers used data management using region of interest for point cloud processing and object detection from big data in application of culture heritage [16]. Data acquisition using TLS has to be done in many scans to collect the complete object in the scene. In this work, data from St1 to St10 are utilized for evaluation on the effect of radius object interest and radius of obstacle for segmentation performance of ground and non-ground with respect to mean square error, MSE as shown in Table 1. The distance of inliers to fits the ground for outdoor scan station (St1- St5) give more error, 0.0468m due to higher altimetric variations compare to indoor scan station, 0.0374m. As the exterior scans contain lower number of building point cause difficulty to precisely cite the building shapes [17]. But, from results shows in Figure 5, this method has managed to segment ground plane, Bell tower and trees in green, black and blue colour respectively. Red colour near the Bell Tower shows obstacle that surrounded the object of interest (i.e. the tower).

| Scan station | Number of points | Radius of obstacle, r1 | Radius of object interest, r2 | Sensor location, s | Mean square error, MSE (m) |
|--------------|------------------|------------------------|-----------------------------|--------------------|--------------------------|
| St1          | 937985           | 8                      | 6                           | (-5, 5, 0)         | 0.0402                   |
| St2          | 1044604          | 8                      | 6                           | (-5, 5, 0)         | 0.0557                   |
| St3          | 1257631          | 8                      | 6                           | (-3, 3, 0)         | 0.0599                   |
| St4          | 1025035          | 8                      | 6                           | (-1, -5, 0)        | 0.0416                   |
| St5          | 1139172          | 8                      | 6                           | (-4, 6, 0)         | 0.0367                   |
| Average of mean square error for outdoor scan | 0.0468 |

| St6          | 2458917          | 7                      | 5                           | (0, 2, 0)          | 0.0336                   |
| St7          | 2470413          | 7                      | 4                           | (0, 2, 0)          | 0.0373                   |
| St8          | 2368642          | 7                      | 4                           | (0, 3, 0)          | 0.0467                   |
| St9          | 3716494          | 6                      | 4                           | (1, -1, 0)         | 0.0355                   |
| St10         | 3752373          | 7                      | 5                           | (1, -0.5, 0)       | 0.0338                   |
| Average of mean square error for indoor scan | 0.0374 |
6. Conclusion and future work
In this research, point cloud data of Tawau Bell Tower or the Belfry is treated as the object of the interest to study the usage of RANSAC and localization in segmenting ground and non-ground data. The ground plane and non-ground objects were able to be segmented using RANSAC approach. Data reduction implemented by limiting the range of each axis has managed it to only highlighting region contains information of the building and nearby entities. Moreover, we apply reference point location for bounding box to trace the Bell Tower as the extended approach to RANSAC algorithm. In conclusion, our method has able to segment ground plane and the object of interest.

Some future work can further be studied to improve the algorithms where overlapping area between object and obstacle required detail assessment for actual structure. Moreover, other geometrical constrain can help in defining the boundary of the object of interest. Extended data structure also can be utilised to speed up processing time.

7. Acknowledgment
The authors would like to acknowledge the support from the Fundamental Research Grant Scheme (FRGS) under a grant number of FRGS/1/2017/ICT04/UNIMAP/02/1 from the Ministry of Education Malaysia.

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