Performance analysis of different classifiers in segmenting point cloud data

N I Boslim¹, S A Abdul Shukor¹*, S N Mohd Isa¹, R Wong²

¹Faculty of Electrical Engineering Technology, Universiti Malaysia Perlis, 02600 Perlis, Malaysia
²Geodelta Systems Sdn. Bhd., 22 Jalan SS20/11, Damansara Utama, 47400 Petaling Jaya, Selangor, Malaysia

*E-mail: shazmin@unimap.edu.my

Abstract. 3D point clouds are a set of point coordinates that can be obtained by using sensing device such as the Terrestrial Laser Scanner (TLS). Due to its high capability in collecting data and produce a strong density point cloud surrounding it, segmentation is needed to extract information from the massive point cloud containing different types of objects, apart from the object of interest. Bell Tower of Tawau, Sabah has been chosen as the object of interest to study the performance of different types of classifiers in segmenting the point cloud data. A state-of-the-art TLS was used to collect the data. This research’s aim is to segment the point cloud data of the historical building from its scene by using two different types of classifier and to study their performances. Two main classifiers commonly used in segmenting point cloud data of interest like building are tested here, which is Random Forest (RF) and k-Nearest Neighbour (kNN). As a result, it is found out that Random Forest classifier performs better in segmenting the existing point cloud data that represent the historic building compared to k-Nearest Neighbour classifier.

1. Introduction
Throughout recent years, 3D laser scanning technology has been applied in a wide range of fields, with the growing development in computer science and information technology. One of the laser scanners available is the Terrestrial Laser Scanner (TLS) which is typically used to gather information of big scene and object of interest like a building. It able to generate extremely accurate and reliable 3D point cloud details from the subject [1][2]. Nevertheless, due to the size of scenery and object, data may be collected in many stations of TLS which will contribute to a large file size. Ultimately, the data collected not only represent the building, but also the surrounding elements like trees and other structures. This is because of the TLS scanning capability which covers 360 degree. In order to get the only data of the object of interest, we need to segment the collected data. Hence, classifier is required to segment the point cloud.

Nowadays, there are a lot of classification methods available. Two commonly used classifiers in point cloud data processing are Random Forest (RF) and k-Nearest Neighbour (kNN). RF classifier is implemented with geometric and contextual characteristics for semantic labelling. The data are segmented into groups with similar properties. This algorithm was used in a wide range of
applications, including segmenting buildings like homes, classrooms, a warehouse [3]. RF has also been used to classify other types of data in fruit diseases application [4].

k-Nearest Neighbour (kNN) has attracted much more interest from many researchers for pattern identification and machine learning [5]. KNN classifier effectively determine the class label of the query samples by using the parameter k of the neighbourhood size and the simple majority vote among k-Nearest Neighbour. kNN classifier has been applied in many applications involving feature selection and dimensionality reduction. Previous research [6] stated that the kNN is an intuitive and effective non-parametric model in segmentation. kNN is used in [7], to segment vehicle types (car and motorcycle) from 3D point cloud data.

In this paper, the performance of these two main classifiers commonly used in segmenting point cloud data, which are RF and kNN will be compared and analysed. Data used in this project represents a scene of historical building in Sabah, Malaysia, collected using a TLS. Analysis on the workability of the classifiers in segmenting the object of interest, i.e., the building, is done using MATLAB software, and it is hope that the results could help other researchers working in the similar area of interest (i.e., point cloud data segmentation).

2. Methodology

2.1. Data collection

In this research, the data is provided by Geodelta Systems Sdn. Bhd. Terrestrial Laser Scanner (TLS) of Leica HDS6000 with a field of view of 360 degrees horizontally and 270 degrees vertically is used. The building of interest is the Bell Tower Tawau, Sabah. The tower, also known as Belfry Tower, is located in Tawau, Sabah and was constructed as the evidence of British government before Sabah became part of Malaysia. Figure 1 shows the Belfry Tower.

Figure 1. The Belfry Tower, Sabah

2.2. Data pre-processing

The amount of point cloud data gained by the laser scanner is quite large and also contains surrounding area that can be treated as noises and outliers, that may affect the reconstruction process of the historical building later on. Thus, a filter has been used to minimize the noise and making the point cloud data cleaner. The chosen filter in this work is “pcdenoise” filter function [8]. “pcdenoise” function removed unwanted data from the raw data and provides a better visual of data. This function is developed and used based on work by [9] and it is used because of its versatility and ease of usage
in MATLAB when processing point clouds. Figure 2 shows the original, raw point cloud data while Figure 3 shows the results of applying "pcdenoise" function to the raw data. The ground data (blue-black) is then removed to produce smaller size of data for easier segmentation process.

2.3. Data segmentation

The two chosen classifiers, RF and kNN, were used to segment the building of interest, i.e., the Belfry Tower, from other surrounding data. Prior to the segmentation, the data is clustered into building and non-building data.

Firstly, RF classifier is used. RF classifier uses a classification learning method for a group that uses several decision trees and produces average tree predictions. This classifier generates forests with random number of trees. Normal decision tree algorithms based on rules for data set prediction is utilised. RF finds the root node and randomly split according to the features. Figure 4 shows the working principle of the classifier [10], where $x$ represents the input to the classifier, which is in this case, the pre-processed point cloud data. Random decision trees are generated namely $tree_1$, $tree_2$, ..., $tree_B$, whose corresponding outputs are $k_1$, $k_2$, ..., $k_B$. Majority voting is conducted, and class $k$ is selected from $k_1$, $k_2$, ..., $k_B$, and will be the output of the classifier.

Next, test on another classifier which is kNN is conducted. kNN classifies data on closest distances and indices depending on the k-value. Distances based on Euclidean which is usually adapted in point
cloud data processing were determined from the query points and its nearest neighbours to segment the data. The k-value must be carefully selected. If the k-value is too low, it will be too noise-sensitive, while if the k-value is too large, the segmentation may not be performing well. In this work, k is defined as 1 after several experiments in finding the suitable value.

2.4. Analysis of performance
To analyse the performance of these two selected classifiers, both quantitative and qualitative analysis were used. For quantitative analysis, several measurements towards the original height and width of the building with respect to the segmentation results were compared and accuracy was determined using Equation 1, where segmentation measurements are taken from the results of respective classifier and original measurements are taken from the as-built drawing of the tower. Then, visualization comparisons were done to see the performances with respect to qualitative analysis.

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\text{Accuracy} = \frac{\text{Segmentation measurement}}{\text{Original measurement}} \times 100
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3. Results and Discussion
Figure 5 shows the final segmentation result by using kNN classifier, while Figure 6 shows the results of RF classification. Qualitatively, it can be seen that RF produced better visualization when segmenting the building data compared to kNN, where small part of other entity of the nearby tree were also included in the classification. To analyse further, dimensions of height and width representing the building were taken and compared with the original measurement. Table 1 shows the original measurements of the tower’s height and width together with the segmentation measurements respectively, and Table 2 summarised the accuracy analysis calculated from Equation 1. It can be seen that RF produces better results compared to kNN in segmenting Bell Tower point cloud data from its environment.

![Figure 5. Result of kNN classifier](image1.png)

![Figure 6. Results of RF classifier](image2.png)
Table 1. Measurements of Bell Tower

| Measurement | Height (m) | Width (m) |
|-------------|-----------|-----------|
| Original    | 10.590    | 5.147     |
| kNN         | 8.926     | 4.468     |
| RF          | 9.567     | 4.511     |

Table 2. Accuracy analysis (%)

| Classifier | Height | Width |
|------------|--------|-------|
| kNN        | 84     | 87    |
| RF         | 90     | 88    |

4. Conclusion
This paper analysed on the performance of two selected classifiers, RF and kNN, in segmenting 3D point cloud data of a historical building in Sabah, Malaysia from a TLS. RF shows better performances qualitatively and quantitatively in segmenting the object of interest, i.e., the building data from other data surrounding it. More work can be done towards other point cloud data or segmenting the data into more than one groups / classes to analyse the classification method further.

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