Indoor Mapping Using Machine Learning Based Classification of 3D Point Clouds

Alper Sen*, Atakan Bilgili*

* Department of Geomatic Engineering, Faculty of Civil Engineering, Yildiz Technical University, Esenler, Istanbul 34220, Türkiye
alpersen@yildiz.edu.tr, atakanb@yildiz.edu.tr

Abstract. Today, indoor maps remain a valuable source of spatial information for various indoor environments. Classifying 3D point clouds from indoor environments is crucial for indoor mapping. In this study, indoor point clouds from the S3DIS dataset were classified using Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Multi-Layer Perceptron (MLP), and Attentive Interpretable Tabular Learning (TabNet). The classification performances, based on overall accuracy and F1 scores, can be ranked as RF, MLP, XGBoost, and TabNet. It has been determined that machine learning algorithms can be used to classify indoor point clouds for indoor mapping.

Keywords. Indoor mapping, machine learning, point cloud

1. Introduction

The automatic generation of high-quality indoor maps for existing buildings poses a significant challenge within navigation automation, virtual reality, and robot object manipulation (Lin et al 2021). Since the as-built condition of the buildings often deviates from the original plans due to renovations, indoor mapping for existing buildings has garnered extensive research attention. Indoor maps can be considered as the output of indoor measures and serve as the foundation for most indoor-based applications. The complexity of buildings and the increasing use of indoor positioning systems also provides a strong motivation to enhance the cartographic representation of indoor maps (Nossum 2013).

Indoor mapping data acquisition refers to the measurement techniques, sensors, media, and platforms used to obtain raw data from indoor environments. The main components in acquiring indoor mapping data are hardware for data processing and sensor synchronization, typically a mapping sensor such as LiDAR (Light Detection And Ranging) or an RGB-D (Red, Green, Blue - Depth) camera (Otero et al. 2020). In this study, a backpack-

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shaped mobile laser scanning system, in collaboration with our university, was used for acquiring indoor point data. The components of this device include GPS, LiDAR, camera, processor, battery, interface, and other connection elements.

The classification of 3D point clouds belonging to indoor environments plays a significant role in the generation of indoor models (Lin et al 2021). Significant progress has been made in the recognition of point clouds belonging to outdoor environments. However, recognizing indoor scenes remains a challenge due to their confined surroundings, various structural features, and numerous obstacles such as columns and walls (Hangbin et al. 2020). In recent years, the classification of indoor point clouds using deep learning algorithms has been an active research topic. The classification performances of different deep learning algorithms on the Stanford 3D Indoor Semantics (S3DIS) dataset (Armeni et al. 2016), generated by Stanford University, were provided in the study by Lin et al. (2021).

The performance of machine learning (ML) methods in the classification of indoor point clouds for high-quality indoor mapping is one of the current research topics. In this study, indoor point clouds from the S3DIS dataset were classified using RF, XGBoost, MLP, and TabNet. It has been observed that the classes of ceiling, wall, and column, which have been classified with high performance, can be utilized for indoor floor maps. We have thus conducted preliminary work on the indoor mapping of point clouds obtained from our university, by utilizing the indoor mapping of a similar dataset such as S3DIS.

2. Methodology

Steps of the proposed study (see Figure 1): (1) Preprocessing of the S3DIS indoor point cloud dataset, (2) normalization of the point cloud data, (3) classification using ML methods, (4) evaluation of classification performance, (5) determination of object classes classified with high performance for automatic generation of indoor maps in GIS environment.

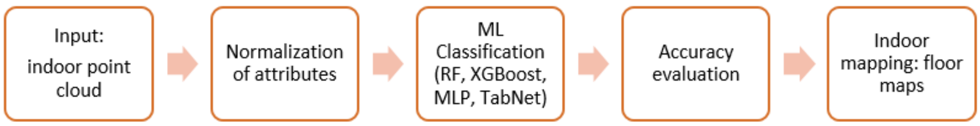

Figure 1. The framework of the study.

2.1. Preprocessing (Input and Normalization)

The classes in the S3DIS were labeled as the ceiling, floor, wall, door, window, column, table, chair, board, clutter, bookcase, sofa and beam in a discrete file format. To prevent the overfitting problem, classes were combined to create a balanced dataset. For the purpose of creating indoor maps, the classes were merged in the training and test data as follows: wall, door, window, column, and board were merged into one class (merged class-1), and bookcase, table, chair, and clutter were merged into another class (merged class-2). In total, 4 classes were obtained (ceiling, floor, merged class-1, and merged class-2). An office was used for the training (70%) and test data (30%) and 30 different offices were classified. 3D coordinates *x, y, z*, and RGB values are the attributes we used as inputs to the ML algorithms. Input vectors were scaled linearly by min-max normalization.

2.2. Machine Learning Classification

In this study, we used four ML algorithms: MLP, RF, XGBoost and TabNet. MLP is a feedforward artificial neural network. MLP is a highly popular supervised ML algorithm and forms the basis of widely used deep learning algorithms (Han et al. 2012). RF is a powerful ensemble learning method that combines multiple individual decision trees to make predictions (Breiman 2001). XGBoost is a popular boosting-based ML algorithm (Chen and Guestrin 2016). TabNet combines ideas from deep learning and attention mechanisms to effectively learn representations from tabular data and make predictions (Arık and Pfister 2020).

2.3. Accuracy Evaluation

Evaluating the prediction performance of an ML model, which is tuned with several hyperparameters defined in a search space, is an important part of the classification process. In the literature, several metrics exist for assessing the prediction performance of an ML classifier. In this study, the performance of ML models was evaluated using four evaluation metrics: accuracy, recall, precision, and F1 score.

2.4. Indoor Mapping

After the classification of indoor point clouds, polygons were obtained from the intersections of the ceiling and merged class-1 to create floor maps. Since the objects on the floor and in front of the wall create gaps (missing data) in the floor and wall classes, the floor polygons obtained from the intersections of the ceiling and merged class-1, and lowered by the wall height. The polygons belonging to the rooms and corridors were merged to obtain floor maps. In Figure 2, a sample point cloud obtained from a backpack-shaped mobile laser scanning system and a generated indoor map are given.

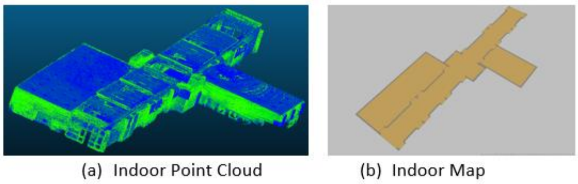

Figure 2. Indoor point cloud of a university building obtained from our mobile laser scanning system (a) and its indoor map (b).

3. Results (Preliminary)

In this study, we used Python 3.8.8 and Scikit-learn ML library to classify the point clouds, and ArcGIS Pro 3.1 tools to produce the indoor maps. A preliminary study was conducted on the S3DIS dataset (Area 5) to test the consistency of the methods. The S3DIS dataset is a large-scale indoor point cloud dataset created by Stanford University. An office room was used for training and test data, and 30 different office rooms were classified. The accuracy metrics of the best test accuracy result (in 120 experiments: 30 spaces x 4 methods) are given in Table 1. The initial results showed that the RF method achieved an average accuracy of 86% and F1 scores of 89% for the ceiling, 97% for the floor, 90% for merged class-1, and 62% for merged class-2. The MLP method achieved an average accuracy of 85% and F1 scores of 92% for the ceiling, 97% for the floor, 87% for merged class-1, and 60% for merged class-2. The XGBoost method achieved an average accuracy of 85% and F1 scores of 86% for the ceiling, 96% for the floor, 89% for merged class-1, and 60% for merged class-2. Lastly, the TabNet method achieved an average accuracy of 83% and F1 scores of 93% for the ceiling, 82% for the floor, 87% for merged class-1, and 58% for merged class-2. Ground truth, RF classification (in Table 1) and floor map of an office room are illustrated in Figure 3.

ML Classifier	Office Room	Precision	Recall	F1 score	Accuracy
RF	Ceiling	0.98	0.98	0.98	0.93
	Floor	0.98	1.00	0.99	
	Merged Class 1	0.93	0.95	0.94	
	Merged Class 2	0.80	0.73	0.77	

Table 1. The accuracy metrics of the best test accuracy in 120 experiments (30 spaces x 4 methods).

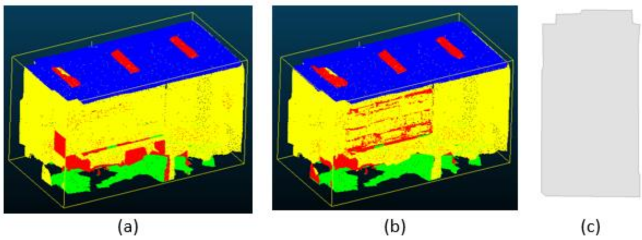

Figure 3. Ground truth (a), RF classification (b), and generated floor map (c) for an office room in the S3DIS dataset.

4. Conclusion

Classifying 3D point clouds from indoor environments is crucial for indoor mapping. The classification performances, based on overall accuracy and F1 scores, can be ranked as RF, MLP, XGBoost, and TabNet. However, the ML classification with the highest performance for each class can be utilized in hybrid solutions. In this study, it has been determined that ML classification can be used to classify indoor point clouds for indoor mapping. As a result, preliminary findings have been obtained regarding the generation of indoor maps for the test buildings of our university campus.

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