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# Point cloud classification using machine learning algorithms and selection of relevant features

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**Abstract**

3D scene classification has become an essential task in photogrammetry, remote sensing, computer vision, and robotics. Point clouds are a data source containing geometric information for 3D world representation. Successful classification results are obtained using the point cloud's geometric information. Machine learning approaches are widely used for point cloud classification. In this study, point cloud classification was performed using random forest (RF) and support vector machine (SVM) algorithms. Geometric features are used to describe each point in the point cloud. However, not every feature may have the same effect on classification. For this reason, the most effective features were determined by applying the filter-based feature selection algorithm. As a result of feature selection, the F1-score value obtained with RF increased by 5.7%, and the F1-score value obtained with SVM increased by 16%.

## 1. Introduction

Three-dimensional (3D) point clouds are widely used in many applications such as urban geometry mapping, autonomous driving, virtual reality, cultural heritage, augmented reality, as they present the 3D representation of the environment with high precision (Bello et al., 2020; Atik and Duran, 2022). In particular, they provide more information about the structure of objects than 2D images, thanks to the 3D geometric information they contain.

Point cloud classification has become a focus of researchers over the past decade. Machine learning approaches have come to the fore because traditional rule-based approaches are insufficient for classification of complex and large point clouds. Machine learning algorithms provide powerful mathematical tool that can be used to segment large and complex point clouds. The discriminating rules are learned automatically from the training data in machine learning (Atik et al., 2021).

For machine learning approaches, features that define a point must be provided as input. Geometric features produced using the 3D geometry of the point cloud distinguish a point. However, not every input feature has the same effect on classification. Many feature selection algorithms have been proposed in the literature to identify the most relevant features (Wu et al., 2013). Thus, it is aimed to improve the point cloud classification performance of machine learning approaches.

In this study, point cloud semantic segmentation was performed by machine learning using geometric features. Experiments were carried out using the mobile LiDAR dataset Oakland3D. Random Forest (RF) and Support Vector Machine (SVM), two popular machine learning algorithms, are preferred as classifiers. Filter-based Information Gain (IG) algorithm is used as a feature selection algorithm.

## 2. Data and Method

### 2.1. Oakland3D Dataset

Oakland3D dataset (Munoz et al., 2009) is one of the most used datasets obtained from mobile platform and includes urban environment. The Oakland dataset consists of 36,932 training points, 91,579 validation points and 1.3 million testing points, which include 5 classes, namely ground, vegetation, façade, wire and pole/trunk. The wire and pole/trunk classes were removed, so they contain a few points. A sample from the dataset is shown in Fig. 1.

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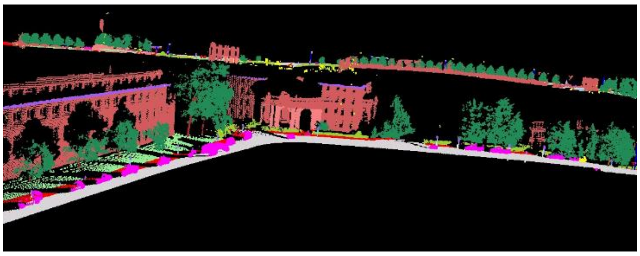


**Figure 1.** Sample from Oakland3D dataset

## 2.2. Random Forest

Random Forest (RF) (Breiman, 2001) is a machine learning approach that consists of uncorrelated trees and averages these trees. In many problems, the performance of random forests is easily increased. Each tree generates a prediction, and the class with the most votes is assigned the model's prediction. A sub-dataset is assigned to each tree for training in the bagging algorithm.

Two parameters are required to generate a tree with the RF classifier. These parameters are the number of variables used in each node and the number of trees to develop to determine the best split.

## 2.3. Support Vector Machine

Support Vector Machines (SVM) (Cortes and Vapnik, 1995) is a supervised machine learning algorithm used for both classification and regression. The main purpose of SVM is to classify the data by finding the hyperplane with the maximum distance between the data points of both classes. The optimal hyperplane can be obtained by using Eq. 1. For a given set of a sample $x_i$ (i=1,2,..., N):

$$f(x) = w^T x + b = \sum_{j=1}^{N} w_j x_j + b = 0 \qquad (1)$$

where *w* is an *N*-dimensional vector and *b* is a scalar, and they are used to define the hyperplane.

## 2.4. Extraction of Geometric Features

Geometric features are used to describe the local geometry of a point in the point cloud. Geometric features are calculated by the eigenvalues ($\lambda_1$, $\lambda_2$, $\lambda_3$) of the eigenvectors ($v_1$, $v_2$, $v_3$) derived from the covariance matrix of any point p of the point cloud:

$$cov(S) = \frac{1}{S}\sum_{p \in S}(p - \bar{p})(p - \bar{p})^T \qquad (2)$$

where $\bar{p}$ is the centroid of the support S (Weinmann et al., 2015). Calculated features are the sum of eigenvalues, omnivariance, eigenentropy, anisotropy, planarity, linearity, surface variation, sphericity, and verticality.

## 2.5. Feature Selection with Information Gain

Some features have a greater impact on the semantic segmentation of the algorithm, while others do not. Feature selection is defined as the task of determining the minimum number of features that will accurately represent the data. Feature selection methods can be grouped as filter-based, wrapper-based, and embedded methods. Both wrapper-based and embedded methods depend on classifier algorithms. Filter-based methods are independent of the classifier (Weinmann et al., 2015).

Information Gain (IG) is an entropy-based feature selection algorithm and measures the amount of information provided by features. It is widely used in the literature for text classification (Lei, 2012).

## 2.6. Experiment

Geometric features were calculated for the training and test data. Geometric features are calculated using neighboring points falling into the sphere with a certain radius around the point. In this study, the sphere radius was determined as 1.5 m. This value is the optimum value determined for the Oakland3D data set in previous studies.

The training parameters determined for RF are maximum depth 100, random state 100 and minimum sample split 80. The parameters determined for SVM are kernel radial basis function (RBF) and decision function one-vs-rest (ovr). Values were determined experimentally.

Classification was performed using all features with RF and SVM algorithms. Then, the semantic segmentation process was repeated using 5 features determined by IG. F1 score was used as evaluation metrics. For the experiments, i7-11800H, 2.30 GHz processor, GTX 3070 graphics card, and 32 GB RAM hardware was used.

# 3. Results and Discussion

Feature importance values were calculated with IG using the entire training set. A threshold value of 0.7 has been determined for feature selection. Five features with importance greater than 0.7 were selected as the most relevant feature: surface variation, normal change rate, sphericity, anisotropy and verticality. Feature importance values and selected features are shown in Fig. 2.

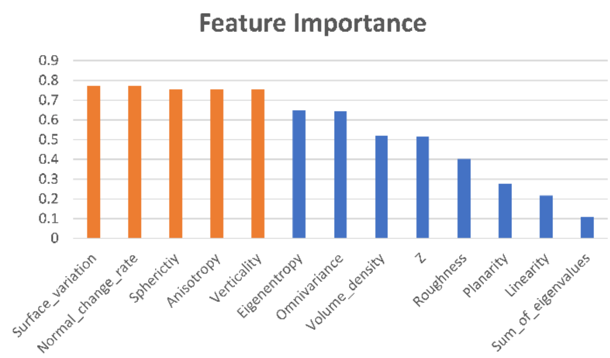
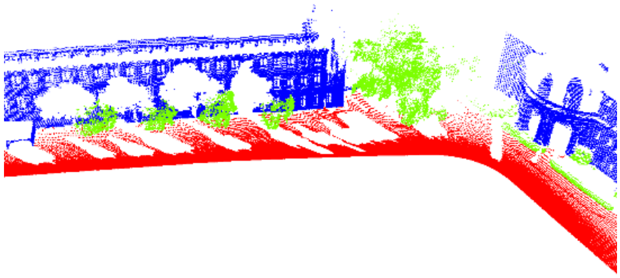



**Figure 2.** Calculated feature importances with IG. Selected features are marked as orange

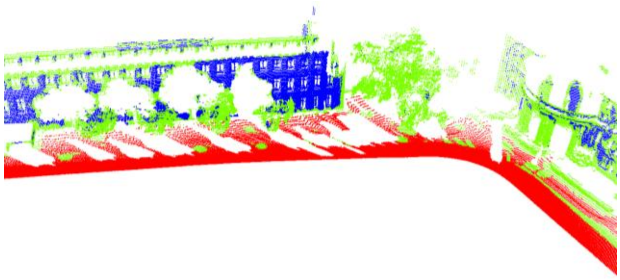
When all features were used, 86.6% and 77.4% F1-scores were obtained with RF and SVM, respectively. With both algorithms, less accuracy was obtained in the building than in vegetation and ground. When Table 1 is examined, it is revealed that feature selection significantly improves the semantic segmentation performance of RF and SVM. The average F1-score of the RF increased by 5.7%, while the average F1-score of the SVM increased by 16%. Feature selection provided the highest improvement in the building class. It was concluded that not all geometric features have the same effect. The results are presented in Table 1. Classified point clouds are shown in Fig. 3.

**Table 1.** F1-score of the algorithms based on features.

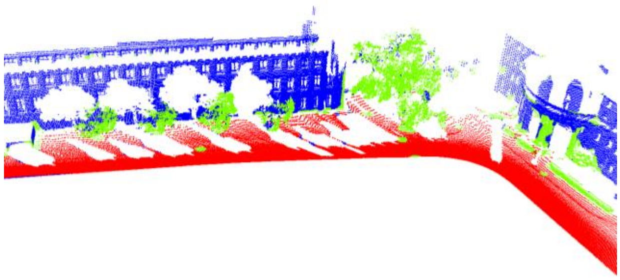
| | All Features | | Selected Features | |
|---|---|---|---|---|
| **Class** | **RF** | **SVM** | **RF** | **SVM** |
| Building | 73.6 | 67.0 | 85.9 | 88.3 |
| Vegetation | 87.5 | 83.2 | 91.6 | 92.6 |
| Ground | 98.6 | 82.0 | 99.3 | 99.3 |
| Average | 86.6 | 77.4 | 92.3 | 93.4 |



(a)



(b)



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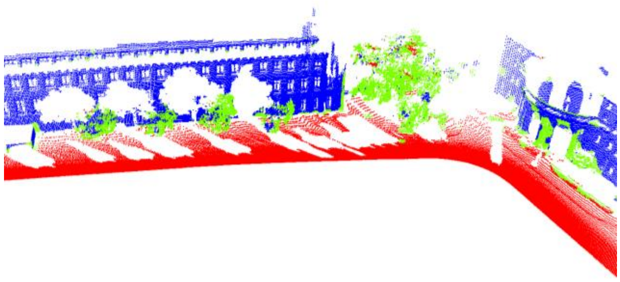
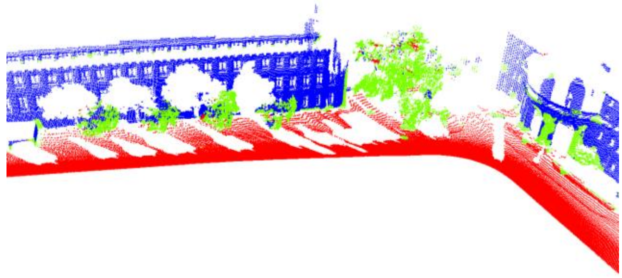


(d)



(e)

Building Vegetation Ground

**Figure 3.** Classified point clouds. (a) Ground truth Prediction with RF using all features; (c) Prediction with SVM using all features; (d) Prediction with RF using selected features; (e) Prediction with SVM using selected features

## 4. Conclusion

In this study, research on improving the point cloud classification performance of machine learning algorithms by feature selection is presented. The most effective geometric features on classification were determined by the filter-based IG algorithm. Classification performances of RF and SVM algorithms have increased thanks to feature selection.

In future studies, datasets and algorithms obtained from different sensors can be used. In addition, feature selection algorithms can be integrated with deep learning networks.

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